# Essays on the global oil market

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# Contents

# Declaration

I hereby declare that except where specific reference is made to the work of others this dissertation reflect my own work. The first chapter of the thesis is titled “Modelling the global price of oil: is there any role for the oil futures-spot spread?” by Daniele Valenti (L.A.S.E.R. Doctoral School, Universities of Milan, Pavia and Brescia). The second chapter is titled “Interpreting the oil risk premium: do oil price shocks matter?” by Daniele Valenti, Matteo Manera (University of Milan-Bicocca) and Alessandro Sbuelz (Catholic University of the Sacred Heart, Milan). In particular sections: 2.3 Data and stylised facts on the crude oil futures market, 2.4 Econometric method, 2.5 Empirical results and 2.6 Robustness checks reflect my own work. The rest of the chapter is a joint with the other two authors.

# Acknowledgments

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# Introduction

Nowadays, the influence of the price of crude oil on the world economy is indisputable.
As reported by the US Department of Energy Information Administration (EIA), in 2017 the total crude oil consumption amounted to 35.9 billion barrels of oil, and the North Sea Brent crude oil spot prices averaged 54 dollars per barrel.
As a result, the overall oil market size reached 1.9 trillion dollars in the previous year.
Given the growing flow of money into the crude oil market, understanding the economic factors behind oil price movements provides a useful content resource for institutional and private organizations.
For example, central banks can take accurate actions with respect to monetary policy, while private companies can provide more reliable budgets for businesses strategies.
The international market for crude oil involves a pool of traders from different countries around the world and it includes spot and forward markets. The former generally refers to a short-term commodity transaction where the barrels of oil change hands very quickly after the sellers receive payment. The latter consists of contracts through which oil traders agree up-front on a price for a

certain amount of oil barrels that will be delivered to a specific location in the future.

Given the large number of participants in oil markets, it is widely accepted that the price of oil is being determined by worldwide supply-and-demand. The empirical specifications for modelling the price of oil can be divided into two groups: financial and economic fundamentals models. The former investigate the relationship between spot and futures prices in the forward market, whereas the latter analyse the role of aggregate variables to capture the peculiar characteristics of the physical market.

A common practice among researchers is to consider the endogeneity of the price of oil with respect to the economy. In economic fundamentals models, the first analysis to take up this feature is a study by Kilian (2009). The author introduces a Structural Vector Autoregressive (SVAR) model for the global market for crude oil, which represents a novelty in terms of methodology and results.

The SVAR model is based on monthly past data on three aggregate variables: global oil production, a measure for real economic activity and the real price of crude oil. The main finding of this study is that shocks to demand and/or supply have a different impact on the real price of oil.

A revised version of this model is discussed by Kilian and Murphy (2014) and Kilian and Lee (2014), where the authors include a proxy for above-ground oil inventories to capture the forward looking behaviours of oil traders.

My dissertation, “Essays on the global oil market” adds to the above literature, by presenting new empirical evidence. The first chapter of the thesis, “Modelling the global price of oil: is there any role for the oil futures-spot spread?” proposes an analysis of the global market for crude oil based on the revised version of the SVAR model introduced by Kilian and Murphy (2014).

The interesting feature of this model for the context presented above is that it captures the forward-looking expectations of oil traders by replacing a physical proxy for crude oil inventories above the ground with a financial measure, namely the oil futures-spot spread.

The second chapter, "Interpreting the oil risk premium: do oil price shocks matter?", focuses instead on the impact of oil price shocks on the crude oil risk premium. The latter refers to the average returns that long-investors expect to receive as a monetary reward for non-diversifiable risk in the crude oil market.

Both works focus on the global market for crude oil: while the first chapter studies the main economic and financial factors behind changes in the real price of oil on the basis of the theory of storage, the second chapter investigates the effects of oil price shocks on the crude oil risk premium based on the theory of normal backwardation. Although these two economic theories are not mutually exclusive, the former focuses on the role of the convenience yield (a measure of the tightness of the physical spot oil market) while the latter emphasizes the interaction between hedgers and speculators.

In other words, the first chapter treats the oil futures-spot spread as a proxy for the convenience yield but expressed with an opposite sign. The oil futures-spot spread is observable and establishes a link between oil futures prices and current oil spot prices.

The second chapter provides interesting results for the crude oil risk premium, defined as the expected component of the difference between the oil future spot price and the current oil futures price.

One might think to include a proxy for the convenience yield to investigate the effects of oil prices shocks on the crude oil risk premium. This is not necessary for at least two reasons. First, understanding how unexpected oil price changes might affect the risk premium requires the identification of three main structural shocks, that is shocks to oil production (supply shocks), shocks to the global business cycle (aggregate demand shocks) and shocks to the price of crude oil (precautionary demand shocks). The latter, according to Kilian (2009) and Alquist and Kilian (2010), provide evidence of unexpected changes in the convenience yield, therefore the exclusion of the oil futures-spot spread (or above-ground crude oil inventories) as a measure of the storage market does not invalidate the present investigation.

Second, given the difficulty of interpreting the results economically, as the number of endogenous variables increases it is best to propose the most parsimonious specification of the model. The first chapter of my dissertation brings three main elements of novelty to the existing literature.

First, as opposed to traditional oil market VAR models, I glean the expectations of forward-looking traders from the crude oil futures market by replacing the proxy for global above-ground crude oil inventories with the oil futures-spot spread.

This represents the simplest way to establish a direct link between physical and financial markets within the context of the SVAR model. Therefore, the inclusion of the oil-futures spot spread in the set of endogenous variables addresses some practical issues.

The first concern is to construct a reliable measure that aggregates crude oil stocks stored anywhere on Earth. The second issue refers to the lack of information induced by the incentive to hide some of the crude oil stored for each country. Conversely, the oil futures-spot spread represents a measure that is available in real time and is not subject to revisions.

Second, I propose an economic interpretation of a new structural shock, namely the financial market shock, which is designed to capture a change in the benefit of holding crude oil inventories for reasons not already indicated by the previous three structural shocks of the model.

For example, an unexpected positive financial market shock might be driven by a speculative purchase of oil futures contracts, arbitrage mechanisms used to restore the equilibrium between financial and physical markets, and other forms of incentives that are implemented to keep crude oil off the physical market, causing the spot price of oil to rise.

Third, I highlight the main interesting features of five structural oil market VAR models and the implied identification structures. In addition I propose a simple qualitative method to rank SVAR models of interest on the basis of their impulse response functions.

The main results of the first chapter show that the SVAR model with oil futures-spot spread produces consistent impulse response estimates that are qualitatively similar to analogous studies. On average, shocks to aggregate and residual demands represent the most important drivers in explaining the fluctuation in oil futures-spot spread and real price of oil, respectively.

I find that aggregate demand shocks caused an increase in the price of oil between 2003 and 2008, and that positive financial market shocks also contributed significantly to the increase in oil prices.

This analysis illustrates that between 2002 and 2006 the increase in the oil futures-spot spread, associated with a reduction of the convenience yield, due to inventory build-up, was followed by a rise in the real price of oil.

Finally, a qualitative comparison among different SVAR models of the market for crude oil shows two main findings. First, all of these models are well designed to capture shocks to the demand for crude oil that are triggered by unanticipated changes in the global business cycle. This confirms the role played by aggregate demand shocks, in accordance with Kilian (2009) and Kilian and Murphy (2014). Second, alternative methods of identification based on relaxing zero-restrictions improve the accuracy of impulse response functions, providing a clearer explanation for the transmission of structural shocks to the price of oil.

The second chapter of my thesis adds new evidence to empirical literature on the effects of oil price shocks on the crude oil risk premium. The main research question I aim at answering is whether compensation for risk depends on the type of structural shock in question. In particular: what is the relationship between crude oil risk premium and unexpected rise in the price of oil? On average, what should speculators expect to receive as compensation for the risk they are taking on?

To conduct this analysis, I apply a revised version of the SVAR model of the crude oil market as proposed by Baumeister and Hamilton (2017). The methodology allows us to deal with reverse causality and consider the endogeneity of the crude oil risk premium with respect to macroeconomic and global oil market variables.

The main results stemming from the analysis of the dynamic responses suggest the existence of a negative relationship between the impact responses of the price of oil and the risk premium to shocks of economic fundamentals in the global oil market.

This finding is consistent with the theoretical framework based on the hedging pressure theory, limits to the arbitrage theory and further considerations that will be presented and discussed in this dissertation.

In conclusion, this analysis shows that the historical decline of the risk premium could be modelled as a part of the endogenous effect of shocks to the fundamentals of the global market for crude oil as suggested by Kilian and Lee (2014).

# Chapter 1

# Modelling the global price of oil: is there any role for the oil futures-spot spread?

# Modelling the global price of oil: is there any role for the oil futures-spot spread?

Daniele Valenti

## Abstract

In this paper we develop a Structural Vector Autoregressive (SVAR) model of the global market for crude oil where the forward-looking expectations of oil traders are inferred from the financial markets. Thus, we replace the global proxy for above-ground crude oil inventories with the oil futures-spot spread. The latter is defined as the percent deviation of the oil futures price from the spot price of oil and it represents a measure of the convenience yield but expressed with an opposite sign. The following model provides an economic interpretation of the residual structural shock, namely the financial market shock. This is designed to capture an unanticipated change in the benefit of holding crude oil inventories that is driven by financial incentives. We find evidence that financial market shocks have played an important role in explaining the surge of the real price of oil during the period 2003-2008. We also highlight the main interesting features of five structural oil market VAR models and their implied identification structures. In addition we propose a simple qualitative method to rank different oil market VAR models. The comparative analysis offers evidence that the oil futures-spot spread represents a proper measure to capture the forward looking expectations of oil traders.

**Keywords:** Global market for crude oil; Bayesian SVAR model; Oil futures-spot spread; Oil price speculation

**JEL Codes:** Q40 ,Q41, Q43, E32

## 1.1 Introduction

In this analysis, we evaluate the importance of financial forces in driving the real price of crude oil, by relying on a sign-restricted SVAR model. It is widely accepted that crude oil represents the most important and traded commodity in the world.

As reported by the US Department of Energy Information Administration (EIA), in 2017 the total crude oil consumption amounted to 35.9 billion barrels of oil, and the North Sea Brent crude oil spot prices averaged 54 dollars per barrel [1]. As a result, the overall oil market size reached 1.9 trillion dollars in the previous year. Due to the growing flow of money into the global crude oil market, [2] understanding the economic factors behind oil price movements provides a useful content resource for policy makers and private organizations. For example, central banks can take accurate actions with respect to monetary policy, while private companies can provide more reliable budgets for business strategies. In this work, we propose an analysis of the global market for crude oil based on a revised version of the SVAR model introduced by Kilian and Murphy (2014).

Our study widens the extant literature on modelling the global price of crude oil at least in three directions. First, as opposed to traditional oil market VAR

[1] The spot price is the price at which the barrel of crude oil is immediately available in a given region. The Brent spot price is produced in the North Sea region while the WTI spot price is sent via pipeline to Cushing (Oklahoma).

[2] The global crude oil market includes spot and forward markets. The spot market generally refers to a short-term commodity transaction where the barrels of oil change hands very quickly after the sellers receive payment. Typically, spot sales are surpluses or amounts that a producer has not committed to sell on a term basis. Buyers may also have under-or over-estimated their consumption and may have oil surpluses to sell or shortages. Most of the crude oil traded in the physical markets is usually decided in advance by stipulating one year term agreements. According to Smith (2009) only a small fraction of the total physical trading (5-10%) represents a spot deal between two counterparts. The forward market consists of contracts through which oil traders agree up-front on a price for a certain amount of oil barrels that will be delivered to a specific location in the future. Futures price is the price at which the commodity will be available for delivery at a specified future date and place.

models, we retrieve the expectations of forward-looking traders from the crude oil futures markets by replacing the proxy for global above-ground crude oil inventories with the oil futures-spot spread. The latter, defined as the percent deviation of the oil futures price from the spot price of crude oil, is a proxy for the convenience yield but expressed with an opposite sign.

In general, some OECD countries do not provide reliable and regular estimates about their level of inventories and data collections from non-OECD economies are publicly unavailable. In this context the aggregation of world crude oil inventories is a big challenge.

To solve this issue, Kilian and Murphy (2014) introduce a proxy for the global above-ground crude oil stocks by multiplying data of the US crude oil inventories and the ratio between the OECD and the US petroleum stocks. [3]

As pointed out by Kilian and Lee (2014) this proxy fails to take into account the existence of crude oil inventory stored at sea, in transit via pipelines, in the oil tankers and most important in those countries outside OECD regions. Moreover, even if the most accurate proxy for global crude oil inventories was available it would not address the question of how to deal with the lack of information induced by the incentive to hide some of the crude oil stored in each country.

The oil futures-spot spread can be used to deal with these issues by offering a reliable measure of the benefit of having ready access to crude oil stocks, anywhere they might be. There are several reasons to include the oil futures-spot spread in this analysis.

First, it is available in real time and is not subject to revisions as opposed to a proxy for global crude oil inventories. Second, the oil futures-spot spread

[3] Data for petroleum stocks are provided by the EIA and it includes crude oil as well as strategic petroleum reserves (SPR), unfinished oils, natural gas plant liquids and refined products.

is simple to derive and represents a reliable global market value of storage. Third, the crude oil futures contract with maturity 3-months ensures both the arbitrage-free hypothesis and the forward-looking property of the analysis [4]. As a result, the inclusion of the oil futures-spot spread represents the simplest way to establish a direct link between physical and financial markets within the context of the SVAR model.

The second contribution of this paper consists of the economic interpretation of the residual structural shock, namely the financial market shock. The latter can be derived from the combination between the oil futures-spot spread and a specific set of sign restrictions imposed on the elements of the impact multiplier matrix.

According to the theory of storage, we show that a positive financial market shock reflects an increase in the crude oil futures price relative to the current spot price. This shock drives up the residual demand for crude oil causing the amount of oil-stocks to build-up for reasons not already indicated by the previous three structural shocks of the model.

For example, an unexpected positive financial market shock might be driven by a speculative purchase of oil futures contracts, arbitrage mechanisms used to restore the equilibrium between financial and physical markets, and other forms of incentives that are implemented to keep crude oil off the physical market, causing the spot price of oil to rise.

Finally, this work highlights the main interesting features of five SVAR mod-

[4] It is not surprising that a variety of investors trade paper barrels to exploit facilities in terms of cost-efficient trading, risk management opportunities and oil price discovery. Paper barrels consist of forward contracts which are traded by hedgers and speculators in an anonymous auction through futures brokers. These contracts do not require a physical delivery of the commodity. The New York Mercantile Exchange (NYMEX) and the Intercontinental Exchange (ICE) represent the two most important energy derivatives exchanges for futures, swap and options contracts. Trading is made only for speculation or hedging purposes and these instruments are typically closed out (or rolled over) before their expires dates. In other words in these markets it is not necessary to take the delivery of the commodity.

els for the analysis of the global market for crude oil. We proceed as follow. Firstly, for each specification we provide the economic interpretation of the related identification structure with reference to the implied elasticity of oil demand and oil supply. Secondly, we carry on a pairwise comparison of the benchmark SVAR model [5] and the other specifications. The comparative analysis is based on the impulse responses of the real price of oil and forward-looking variables to each structural shock. Finally, we rank the oil market VAR models according to the accuracy of the impact responses and the plausible values of elasticities.

The rest of the paper is organized as follows. Section 1.2 presents the literature review. Section 1.3 describes the dataset and provides empirical evidence of the relationship between crude oil spot prices and oil futures-spot spread. Section 1.4 discusses the econometric method. Section 1.5 illustrates the empirical results. Section 1.6 provides a comparison and a rank of the benchmark SVAR model and other specifications proposed in this analysis. Finally sections 1.7 and 1.8 offer some robustness checks and conclusions, respectively.

[5] The benchmark SVAR model refers to the oil market VAR model with oil futures spot spread proposed in section 1.4.

## 1.2 Literature review

The empirical literature on modelling the price of oil is based on financial and economic fundamentals models. The former investigate the relationship between oil spot and futures prices in the forward market. The latter emphasise the role of the real aggregate variables [6] to capture the peculiar characteristics of the physical market for crude oil.

In most of the cases the above mentioned models are reduced-form econometric approaches grounded on the economic theory.

Some pioneering articles of the theory of storage are studies of Kaldor (1939); Working (1949); Telser (1958) and Brennan (1958). All of these works postulate that, in the short run, rational economic agents can affect the spot and the futures prices of oil by means of their optimal inventories holding. Pindyck (1994, 2001) points out the strategic importance for companies to have ready access to oil stocks. This provides an efficient way to smooth consumption (or production) and to minimise adjustment and marketing costs incurred in the oil industry.

Numerous studies investigate the main economic and financial factors that affect the global price of crude oil, see Hamilton (2009a,b); Smith (2009); Fattouh et al. (2013); Knittel and Pindyck (2016). These works do not find that financial speculation caused an increase in the spot price of oil, during the period 2003-2008.

For example, Knittel and Pindyck (2016) develop an equilibrium model, describing the relationship between the cash and storage market, to investigate whether the impact of oil price speculation is consistent with data on production, inventory changes, spot and futures prices. Given reasonable assumptions

[6] We refer to aggregate variables such as: the world oil-stock (industrial and government oil inventory levels), global production, consumption and real price of crude oil.

about elasticities of oil supply and demand, they conclude that speculation has not played a relevant role in the sharp increase in oil-prices since 2004.

A recent empirical work proposed by Miao et al. (2017) provides an important contribution to the investigation of the impact of crude oil inventory announcements on derivatives prices. The authors find out that oil futures and options prices respond in a manner that seems to anticipate changes in oil inventory levels.

A common practice among researchers is to consider the endogeneity of the price of oil with respect to the economy, as discussed in Kilian and Lutkepohl (2016). This implies that the real price of oil is being determined by worldwide supply-and-demand. The first analysis to take up this feature is a study by Kilian (2009). The author introduces a SVAR model for the global market for crude oil, which represents a novelty in terms of methodology and results. The model of interest includes monthly past data on three aggregate variables: the growth rate of global crude oil production, a measure of real economic activity based on the cost of shipping in the international commodity markets and the global real price of crude oil. [7]

The econometric approach is based on the idea that real price of crude oil is mainly determined by structural shocks associated with a global supply of oil, a world demand for industrial commodities and an oil market specific demand (or precautionary demand shock). The main finding of this work is that shocks to demand and/or supply have a different impact on the real price of oil.

Kilian and Murphy (2012) investigate the roles of the structural shocks on the real price of crude oil by relaxing the zero-restrictions assumptions postulated by Kilian (2009). For the identification of the structural shocks, the authors

[7] We consider the US refiners' imported acquisition cost (RACi) as a proxy for the spot price in the global market for crude oil. This is available from the web-site of the EIA. For the sake of clarity, in this analysis the terms "spot price of oil" and "real price of oil" are treated as synonyms, unless otherwise specified.

develop a Bayesian SVAR model based on a set of sign restrictions imposed on the elements of the impact multiplier matrix. This analysis provides empirical results that are consistent with the narrative in Kilian (2009).

Lutkepohl and Netsunajev (2014) investigate the causal relationship among world oil production, real economic activity and real price of oil by exploiting heteroskedasticity of the data, for the identification of the shocks.

For this purpose, the authors use a Markov Switching VAR model (MS-VAR) to construct impulse response functions and forecast error variance decomposition. They find out that oil supply shocks have little explanatory power for the changes in the real price of crude oil and the aggregate demand shocks have become less important to explain the variability of oil prices, since the mid 1980s.

A work by Baumeister and Peersman (2013) investigates the dynamic change of the structural forces of the global oil market by exploiting a Bayesian time-varying parameter vector autoregressive model (TVP-VAR) with stochastic volatility in the innovation process.

Their results suggest that the reduction of price elasticity of oil demand and supply represents the main reason behind the recent increase in oil price volatility. In other words, the authors state that the slope of the demand and supply curves have become so steeper that even small perturbations on either side of the market, have caused large changes in price of oil followed by modest variation in their quantities.

Early analysis based on SVAR models have three features in common. First, they include the same set of variables proposed in Kilian (2009). Second, they show that unanticipated shocks to demand for crude oil are the most important drivers in explaining the fluctuations in the price of oil. Third, the implied structural models do not include a proxy for the forward looking behaviour of oil traders. In this case global oil market VAR models could fail to identify the speculative component [8]. Therefore, Kilian and Murphy (2014) introduce a SVAR model by adding to the set of endogenous variables a proxy for the global crude oil inventories above the ground. In this way, the speculative actions of oil players are related to unexpected changes in the demand for storage. In this analysis there is no evidence in support of the argument that speculative activities drove up the global price of oil between 2003 and mid 2008. These results are robust to changes in the proxy for global oil inventories, as discussed in Kilian and Lee (2014).

In contrast to this conclusion, Juvenal and Petrella (2015) investigate the role of speculation on oil prices by adopting a Factor Augmented VAR model (FAVAR). This analysis finds evidence that financialization of commodity markets [9] have played an important role in driving the oil price surge between 2004 and 2008. Notwithstanding, the oil consumption demand, driven by economic activity, remains the main driver to capture the largest fraction of oil price fluctuations.

A work by Lombardi and Robays (2011) includes data on the oil futures prices to identify the speculation activities driven by non-fundamental forces. They use an augmented version of the model proposed by Kilian and Murphy (2014). The identification structure accounts for the existence of a destabilizing financial shock, which is defined as a structural shock that raises instantaneously

[8] As discussed in Kilian and Lee (2014), if the economic agents respond to information about future state of demand and supply of crude oil, which are not currently included in the researcher's information set, the market expectations will differ from those inferred by researcher and this makes the VAR methodology to disentangle the economic fundamentals invalid.

[9] In Fattouh et al. (2013) the authors state that financialization of commodity markets reflects the increasing acceptance of oil derivatives as a financial asset by a wide range of market participants including hedge funds, pension funds, insurance companies, and retail investors.

the oil futures prices and the oil futures-spot spread.[10] The main result by Lombardi and Robays (2011) suggests that the destabilizing financial shocks can affect oil prices in the short run with negligible effects on either production and aggregate demand sides. According to Fattouh et al. (2013), the identification scheme leaves unrestricted the sign of the inventories casting doubts on the validity of all structural shocks.

Finally, a recent study by Baumeister and Hamilton (2017) consists of a Bayesian SVAR model with inventories and measurement error. This work sheds light on the importance of the supply shocks to the real price of oil. Moreover, this analysis provides evidence that structural shocks from supply and demand sides are equally important to drive much of the fluctuations in oil prices during the recent period.

[10]The oil futures-spot spread is defined as the difference between the impulse responses of the futures and spot prices of crude oil.

## 1.3 Data and variables

The following study consists of four monthly aggregate variables based on time-series data that covers the period 1983:3-2016:7.

The global oil production is measured in thousands of barrels of crude oil and is expressed in percent changes.

The real price of oil is constructed from the US refiners' imported acquisition cost of crude oil (RACi) [11] which is deflated by the US consumer price index. In this analysis, the choice of RACi as proxy for the global price of crude oil is motivated by two main reasons. First, according to the extant literature on modelling the global price of oil, the RACi represents the most relevant measure for theories interpreting oil price shocks as terms of trade shocks. This postulates that an unexpected increase in the real cost of imported crude oil triggered by exogenous events typical of global oil markets causes a decline in the aggregate domestic income. This is also consistent with the fact that standard macroeconomic models of the transmission of oil price shocks are specified in terms of cost of imported crude oil, as discussed in Kilian and Vigfusson (2011). Second, the existence of alternative oil price measures, such as the West Texas Intermediate (WTI) and the Brent crude oil spot prices are not representative of the global demand and supply of crude oil. Since, the WTI spot price has been subject to government regulation it would represent a good proxy for the U.S. producer price index but it does not provide an accurate measure for oil price fluctuations in global oil market. The same applies to the Brent spot price of oil which is the main reference for the Northwest Europe oil market.

[11] The refiners' acquisition cost (RAC) for imported crude oil (RACi) can be defined as the average price paid by U.S. refiners for imported. It refers to non-U.S. crude oil booked into the refineries in accordance with accounting procedures generally accepted and consistently and historically applied by the refiners concerned. The RACi includes transportation and other fees paid by the refiner.

For these reasons, the RACi is likely to be a better proxy for the global price of crude oil. Following Kilian and Murphy (2014) we conduct our analysis by taking the real price of oil in log deviation from its sample mean.

The macroeconomic indicator we use for this study is the real economic activity index (REA) as proposed by Kilian (2009). [12] The following measure represents a proxy for changes in the volume of shipping of industrial materials and it is representative for the state of the global economy. According to Kilian and Zhou (2017) the Kilian's index provides four important advantages.

First, the coverage of the index is global because it accounts for the emerging economies like China and India which have played a primary role in determining the demand of industrial commodities since 2000. Second, it is a direct measure because it incorporates shifting country weights. Third, the fact that it is a leading indicator with respect to several real-output measures, such as global real GDP and world industrial production might facilitate the identification of the demand of industrial commodities which are treated as inputs in the production process. Fourth, it is a monthly indicator and its frequency facilitates the economic interpretation of the identification scheme required by SVAR models.

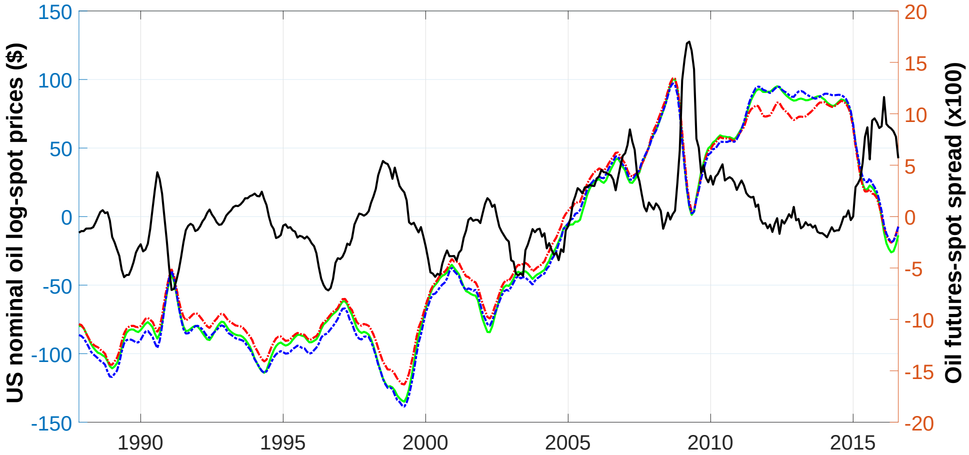
Finally, the oil futures-spot spread is defined as the percent deviation of the

[12] The real economic activity index is available from `http://www-personal.umich.edu/~lkilian/paperlinks.html`. This indicator requires raw data for individual dry bulk cargo freight rates. Following Kilian (2009), the *rea* index can be derived as follows. First, we compute the period-to-period growth rates of each available series. Second, we take the cumulative equal-weighted average of the growth rates, having normalized January of 1968 to unity. Third, the index has to be deflated by the US CPI index. Despite, our analysis starts in 1983 (because WTI oil spot prices are available from that period) we use the original version of the *rea* index. This approach does not undermine the accuracy of our empirical results. We point out that, in 1980, four series are involved for the construction of the index and they remain the same until 1983, the period in which we start our analysis. Therefore, there is not much difference from the cross average of the raw data for individual freight rates and their cumulative average growth rate if the index is constructed starting in 1960 or in 1983. The only difference is the change in the normalization applied to the starting value of the index but this does not compromise the economic meaning of the indicator for the future periods.

futures price [13] from the spot price of oil. To derive the oil futures-spot spread we also include prices from WTI futures market, although the Brent futures contracts are known as the world's crude oil benchmark. The main reason is that, WTI prices allow us to extend the dataset from 1983, since the Brent spot prices became available only in 1986. Therefore for the first period (April 1983 - January 2002) we use futures and spot prices from WTI market with delivery at Cushing, Oklahoma. As regards the second period (February 2002 - July 2016) we use prices from Brent futures and spot markets.

One might be skeptical of the oil futures-spot spread as a reliable proxy for

Figure 1.1: Crude oil spot prices and oil futures-spot spread




*Note:* Blue and red lines denote 6-months moving average of Brent and WTI oil spot prices, respectively. Green line refers to 6-months moving average of US refiners' acquisition cost imported (RACi). Black line indicates the 6-months moving average of oil futures-spot spread.

international crude oil inventories market value. The main reason is that the futures-spot spread is derived from prices referred to some specific locations around the world. With respect to this, we highlight that both WTI and Brent

[13] A monthly measure of oil futures price is the end-of-month value of the last trading day of the futures contract with maturity 3 months. The monthly spot price of oil is derived by taking the end-of-month value of the daily oil spot prices. Both prices are available from Datastream provider.

futures prices represent financial instruments for hedging or speculative actions and they are usually closed out (or rolled over) before their expires date. For this reason the futures contracts are globally traded and their prices are mainly driven by expectations on worldwide oil economic fundamentals. Further, one might argue that the validity of global coverage related to the oil-futures spot spread could be undermine by the presence of different types of oil spot prices. This is not the case because there exist a strong pairwise correlation between the spot prices used to construct the spread and the RACi.

In a storable commodity market, like crude oil, the theory of storage helps to explain the price-setting of some commodities, focusing on the role of stocks, under arbitrage conditions. Basically, the management of oil inventories requires an intertemporal balance between demand and supply of oil. This implies that the value of the inventory changes will depend on the relationship between the current and the expected future spot price.

Figure 1.1 plots the six months moving average of four series: the nominal monthly spot log-prices [14] of WTI, Brent blends, RACi and the oil futures-spot spread. It shows that, if the physical market is subject to an unexpected increase in demand for crude oil, the rise in global spot prices might be likely followed by a reduction in the level of inventories in order to meet the current demand. This causes an increase in the global value of storage which is reflected by the negative of the oil futures spot spread. Thus, oil companies have strong incentives to carry on the optimal management of oil stocks in order to reduce adjustment costs of production and facilitate the delivery of the commodity. As discussed in Pindyck (1994), if a refiner had a small amount of crude oil in its storage it would face with an higher risk of stocks-out and

[14] Time series are available from the web site of the EIA: nominal brent and wti oil spot prices can be downloaded from `https://www.eia.gov/dnav/pet/PET_PRI_SPT_S1_M.htm` while for the imported RAC series the link is `https://www.eia.gov/dnav/pet/pet_pri_rac2_dcu_nus_m.htm`

the benefit of holding an extra barrel of oil would be very high. Conversely if the refiner had a large and full storage of crude oil the benefit accruing from the marginal unit of inventory would decline and the marginal storage cost would increase. This last case would be reflected by a positive value of the oil futures-spot spread. Therefore, it is not surprising to note that increases in the real price of oil are often followed by declines in the oil futures-spot spread, as shown in figure 1.1.

A study of Alquist and Kilian (2010) provides empirical evidence that oil futures-spot spread was highly correlated with cumulative effect of precautionary demand shocks on the real price of oil. The authors show that the pairwise correlation became weaker between 2004 and 2006, raising concerns about the relationship between the financial forward-looking variable and the real price of oil mainly triggered by precautionary demand shocks. The VAR model discussed in the next section offers an economic explanation to changes in the oil futures-spot spread. This is based on the idea that understanding the co-movements between the financial forward-looking variable and the global price of oil requires a structural model that takes into account the endogenous relationship among variables.

## 1.4 Econometric method

In this paper we conduct an empirical analysis of the global real price of crude oil based on the following SVAR model:

$$B_0 y_t = \alpha + \sum_{j=1}^{24} B_j y_{t-j} + v_t \tag{1.1}$$

where $\alpha$ is vector of constant terms [15] and $B_0$ is a matrix capturing the simultaneous relations among the endogenous variables [16] which are collected in the vector $y_t = (q_t, rea_t, p_t, s_t)'$. The set of aggregate variables includes: the percent change in the crude oil production ($q_t$), a measure of cyclical fluctuations in the real economic activity ($rea_t$) as proposed by Kilian (2009), the real price of crude oil ($p_t$) and the oil futures-spot spread ($s_t$). The model reported in this work sets two years' lags [17] and includes dummies variables to remove any seasonality effect. The vector $v_t$ collects the orthogonal structural innovations of the model.

An "oil supply shock ($S$)" is related to unexpected changes in the world oil production. For example, an oil supply disruption is associated with wars and concerns about stability of oil supplies from the Middle East, strategic decisions from OPEC members and other exogenous events in the oil-producing

[15] The seasonal dummies have been suppressed for notional convenience.

[16] This analysis does not include the global proxy for crude oil inventories above the ground for three main reasons. First, we emphasize the original idea of this work where the forward looking expectations of oil traders are inferred from financial side by exploiting the information embodied in the oil futures-spot spread. Therefore the inclusion of the physical forward-looking variable would lead to a redundancy of information. Second, the inclusion of crude oil inventory proxy complicates the identification strategy and the interpretation of the structural shocks. Third, the economic theory suggests that the oil futures-spot spread is not a linear and convex function of the level of inventories, see Fama and French (1987); Pindyck (1994) and Gorton et al. (2013). Therefore, we do not specify a model with both variables (oil futures-spot spread and a proxy for crude oil inventories) because their linear relationship implied by model 1.1 may be a poor approximation.

[17] Applying high lag order (24 months of lags) is relevant to capture the dynamic of the economic business cycle and to allow the model for proper transmission of the structural shocks, in accordance with Kilian (2009); Kilian and Lutkepohl (2016).

countries.

An "aggregate demand shock ($AD$)" is associated with changes in the global demand for crude oil and other industrial commodities mainly driven by fluctuations in the real economic activity. For example, a positive $AD$ shock reflects an unexpected increase in the current demand for crude oil driven by emerging oil-consuming countries.

A "precautionary demand shock ($PD$)" is related to scheduled changes in the convenience yield triggered by uncertainty about shortfalls of expected supply relative to future demand. For example, a positive $PD$ shock reflects an unexpected increase in the demand for storage due to wars, political tensions in the Middle East or other economic factors related to the physical oil markets, as discussed in Kilian (2009); Alquist and Kilian (2010) and Kilian and Murphy (2014).

A "financial market shock ($FM$)"is designed to capture a change in the benefit of holding crude oil inventories for reasons not already indicated by the previous three structural shocks of the model.

For example, an unexpected positive $FM$ shock might be driven by a speculative purchase of oil futures contracts, arbitrage mechanisms used to restore the equilibrium between financial and physical markets, an increase in the global strategic petroleum reserves and other forms of financial incentives that are implemented to keep crude oil off the spot markets.

### 1.4.1 The identification

The estimation of the structural model reported in equation 1.1 follows the algorithm as is typical of the SVAR model identified based on sign restriction discussed in Rubio-Ramirez et al. (2010). Appendix 1.9 provides a description of the estimation and the implementation of the identification strategy. The latter is based on a combination of sign restrictions and bounds on the ratio of the elements of the impact multiplier matrix. Boundary restrictions are often interpreted in terms of contemporaneous price elasticity of oil demand and supply. This procedure allows the identification of a single model among a set-identified structural global oil market VAR models.

### The economic interpretation of sign restrictions

Table 1.1 reports the sign restrictions on the impact responses of crude oil production, economic activity, real price of oil and oil futures-spot spread to each structural shock identified by the SVAR model. The compounded expression of the oil futures-spot spread can be defined as follow:

$$s_t = \frac{F_{t,T} - P_t}{P_t} = r_{t,T} + k_{t,T} - \psi_{t,T} \tag{1.2}$$

where $F_{t,T}$ is the oil futures price observed at time $t$ for delivery at a specified future date $T$, $P_t$ is the spot price of crude oil at time $t$ and $r_{t,T}$ is risk-free interest rate for the period from time $t$ to $T$. Moreover, the marginal cost of storage per unit of inventory is $k_{t,T}$ and $\psi_{t,T}$ represents the marginal convenience yield per unit of storage. [18]

In the theory of storage the notion of marginal convenience yield reflects the flow of benefits accruing from one extra barrel of crude oil and is thought of as a decreasing and convex function of the amount of inventories. It is important to point out that the existence of the marginal convenience yield raises the possibility of the oil futures-spot spread to be negative. This implies that the spot price of oil will exceed the current futures price. A stylised theoretical model in the spirit of Eastham (1939) is discussed in appendix 1.10. This helps

[18] The algebraic sum of $\psi_{t,T}$ and $k_{t,T}$ is known as the convenience yield at net of the cost of storage namely the net-marginal convenience yield.

to motivate the sign restrictions on impact responses reported in table 1.1 and the empirical results presented in section 1.5.

Table 1.1: Sign restrictions on impact responses in the SVAR model

| **Variables & Shocks** | **Negative supply shock** | **Positive aggregate demand shock** | **Positive precautionary demand shock** | **Positive financial market shock** |
|---|---|---|---|---|
| Oil production | - | + | + | () |
| Real economic activity | - | + | - | () |
| Real price of oil | + | + | + | + |
| Oil futures-spot spread | - | - | - | + |

*Note*: All shocks are normalized to obtain an increase in the price of oil. Missing entries mean that no sign restriction on the elements of the impact multiplier matrix is imposed.

An unanticipated oil supply disruption represents a shift to the left of the contemporaneous oil supply curve along the oil demand curve mainly triggered by exogenous events in oil-producing countries.
This shock causes an instantaneous reduction in the global oil production and in the real economic activity followed by an increase in the real price of oil.
In the financial market the futures price will likely rise but by less than the spot price and the effect of the shock on the oil futures-spot spread will be negative, on impact.
An unanticipated positive aggregate demand shock represents a shift to the right of the contemporaneous oil demand curve along the oil supply curve mainly driven by fluctuations in the global business cycle.
This shock causes an instantaneous increase in the real economic activity. Moreover, the unexpected increase in the demand for crude oil will cause the spot price of oil to rise and the oil futures-spot spread to drop. The latter reflects an increase in the marginal convenience yield motivated by the reduction in the level of the inventories in order to mitigate the adverse effects of the shock on the global market for crude oil.

A unanticipated positive precautionary demand shock represents a shift to the right of the oil demand curve along the oil supply curve, mainly driven by an increase in the demand for storage.

The structural shock is designed to capture the benefit of having an extra barrel of oil as insurance against uncertainty about future supply shortfalls relative to expected demand. As pointed out by Kilian (2009), the interruption of the global production of crude oil might happen because of concerns over unexpected growth of demand, over unexpected declines of supply, or over both. In other words this shock coincides with precautionary changes in the level of inventories driven by a scheduled increase in the convenience yield of any given amount of stock.

As a consequence positive precautionary demand shocks cause the oil futures-spot spread to decline and real price of oil to increase, on impact. The following result is consistent with the general equilibrium model discussed in Alquist and Kilian (2010). [19]

An unanticipated positive financial market shock represents an accumulation of crude oil inventories triggered by a rise in the crude oil futures price, for reasons not already embodied by the previous three structural shocks. A positive $FM$ shock causes oil-futures spot spread and real price of oil to rise instantaneously.

As reported in the last column of table 1.1, the impact responses of production and real economic activity to a positive financial market shock is ambiguous. On the one hand, oil producers might increase their level of production if they

[19] Alquist and Kilian (2010) develop a two-country general equilibrium model of the oil futures and oil spot markets in which an oil-producing country exports oil to an oil-consuming country. The authors show that the oil futures-spot spread can be interpreted as an index of shift in expectations about future oil-supply shortfalls. Moreover Alquist and Kilian (2010) prove formally that a sufficient increase in uncertainty about a future oil supply disruption causes a drop of the oil-futures spot spread and an increase in the current real spot price of crude oil, as precautionary demand for crude oil inventories increases.

are interested in earning current profits. On the other hand, they might reduce global oil production, store it and wait to sell crude oil at the highest expected price. Therefore, the accumulation of crude oil inventories might cause an increase in the real price of crude oil followed by a reduction in the real economic activity. Alternatively, the increase in the price of oil triggered by a positive FM shock might also anticipate a global economic expansion, as discussed in Sockin and Xiong (2015).

### The financial market shock

This new shock is designed to capture an instantaneous reduction of the convenience yield (as opposed to a positive precautionary demand shock) and/or a sharp increase in the cost of storage during the inventories' build-up.

Therefore a positive financial market shock represents an instantaneous increase in the oil futures-spot spread followed by a rise in the real price of oil. As a result, this new shock explicitly links the financial and physical markets for crude oil.

For example, let us suppose that some traders bet on the rising price of crude oil. They start buying futures contracts in order to sell them in the future at a higher price, leaving the storage of the commodity to someone else.

By arbitrage mechanisms and ignoring the negligible effects of the interest rate [20] the speculative purchase of futures contracts drives their prices up and causes an accumulation of oil stocks.

The inventory build-up is followed by an increase in the oil futures-spot spread because of a reduction in the marginal net-convenience yield. As a result, the futures prices are greater than current spot prices in order to compensate the

[20] Frankel and Rose (2010) do not provide evidence of a relevant role played by the real interest rate in influencing the price of the commodities.

inventory holders for the high cost associated with storage. Therefore, the financial incentives that are implemented to keep crude oil off the physical market cause an increase in the real price of oil.
The other channel through which a speculative purchase of futures contracts might rise the real price of oil in the spot markets is represented by opposite and simultaneous shifts of both contemporaneous supply and demand curves, as presented in the theoretical model discussed in appendix 1.10 and in Juvenal and Petrella (2015). This case requires a shift to the left of the production curve greater enough to prevail over a shift to the right of the demand curve causing the real price of oil to rise, the global production to decline and the oil-inventories to build-up. The latter is reflected by an increase in the oil futures-spot spread.

**Boundary restrictions**

Following Kilian and Murphy (2014), we start to generate a set of 5 million structural models and retain only those that satisfy all sign restrictions reported in table 1.1.
At this stage we end up with a subset of identified-models. Then we impose on the elements of the instantaneous multiplier matrix boundaries restrictions that are interpreted in terms of impact price elasticity of oil demand and supply.
The impact price elasticity of oil demand [21] must be greater than 0 but lower than -0.8. This last value represents a possible benchmark of the long-run price elasticity as reported by Hausman and Newey (1995). In this work we

[21]The impact price elasticity of oil demand is computed as the ratio between the impact response of global oil production and the impact response of the real price of crude oil to an oil supply shock.

set three times the upper bound [22] of the impact price elasticity of oil supply, originally imposed by Kilian and Murphy (2014). Therefore the new value of short-run price elasticity of oil supply is 0.0774 and is motivated by the following reasons.

First, the authors propose a suggestive value of the supply elasticity which refers to a specific event occurred in August 1990, during the Persian Gulf war. Nevertheless, it is unlikely that the same value could necessarily hold after twenty years. Moreover, studies by Baumeister and Hamilton (2017), Knittel and Pindyck (2016) and Caldara et al. (2017) discuss episodes where some oil producer countries, like Saudi Arabia, could react rapidly to oil exogenous events. All these cases imply a short run supply elasticity even three times grater than the upper bound suggested by Kilian and Murphy (2014).

Second, the short-run oil supply curve should be coherent with all structural shocks. Kilian and Murphy (2014) impose an upper bound for the supply elasticity ignoring the existence of the residual structural shock. It can be shown that such approach yields a set of models where the supply curve is much more elastic in response to residual shock than what implied by the first-three structural shocks.

In our analysis we ensure that the elasticity of oil supply cannot significantly vary across different changes in the global demand for crude oil.

At this step, we end up with a set of models satisfying the sign restrictions on the impact multiplier matrix and the elasticity of oil demand and supply. Moreover, we impose a boundary restriction on the elements of the impact multiplier matrix that is related to the real economic activity. In particular

[22] The identification of the supply elasticity requires an exogenous shift of the demand curve along the supply curve. In order to compute the upper bound of the impact price elasticity of oil supply Kilian and Murphy (2012) compute a ratio between the percentage changes of the global oil production (excluding Iraq and Kuwait) and the percentage change of the oil price increase. The outcome of this ratio is 0.0258 for the period between July and August 1990. All details can be found in the on-line appendix of Kilian and Murphy (2012).

we rule out all cases where the response of real economic activity to financial market shocks are larger than aggregate demand shocks.

The short run price supply elasticity is defined as the ratio between the impact response of the global oil production and the impact response of the real price of oil to each structural demand shock. Therefore, we have three different values of price supply elasticities 0.0774. For the sake of consistency, we focus on that specification that yields the lowest coefficient of variation for the impact price elasticity of oil supply and we select the model satisfying the short-run price demand elasticity closest to the posterior median demand elasticity of the set-identified models. This allows to pin-down a value for the price elasticity of oil demand coherent with the choice of admissible models.

## 1.5 Empirical results

**Impulse response analysis.** In this section we proceed to the analysis of the dynamic responses of the endogenous variables to each structural shock. Figure 1.2 plots the results obtained from the orthogonalized impulse response functions of the SVAR model reported in equation 1.1.

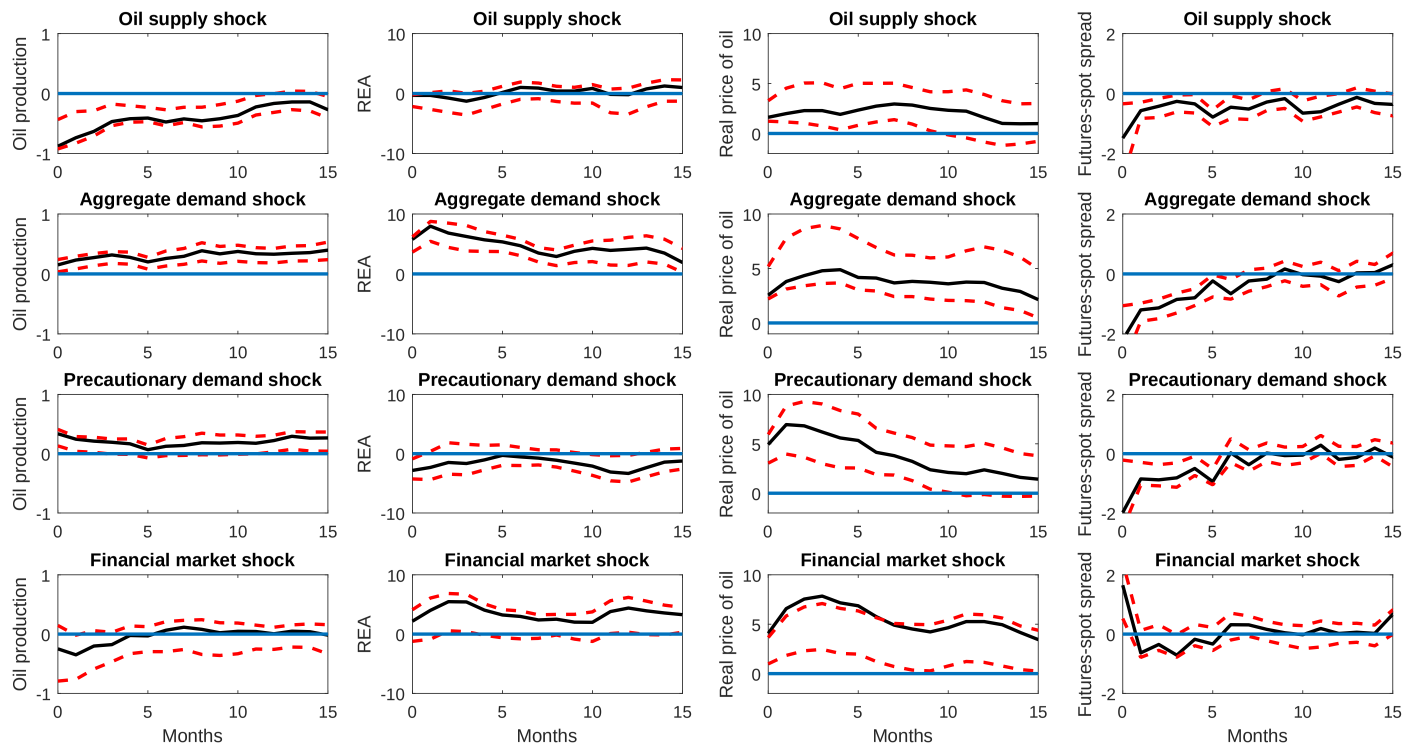
An unexpected oil supply disruption reflects an instantaneous reduction in the global oil production associated with a persistent increase in the real price of oil within the first year. The impact responses of the real economic activity and the oil futures-spot spread to an oil supply disruption is negative. The drop of the financial forward-looking variable reflects an increase in the convenience yield driven by a decline of the crude oil inventories.

An unexpected positive aggregate demand shock causes permanent rises in the real economic activity and in the real price of oil which are followed by a slight increase in the global oil production. The impact response of the oil futures-spot spread is negative as suggested by the economic theory.

An unexpected positive precautionary demand shock causes a sharp increase in the real price of oil. This shock is also associated with a drop in the real economic activity combined with a slight increase in the global oil production. The negative and large response of the oil futures-spot spread to a positive precautionary demand shock is consistent with an upward shift of the convenience yield. Since the benefit of having an extra barrel of crude oil is very high, futures price must be lower than current spot price of crude oil in order to maintain the equilibrium between spot and futures markets.

An unexpected positive financial market shock causes an increase in the oil futures-spot spread and in the real price of oil, on impact. A positive value of the spread reflects a situation where the futures price is greater than corresponding current spot price of oil.

Figure 1.2: Structural impulse responses based on the SVAR model




*Note:* Figure 1.2 plots the path-responses to one-standard deviation structural shocks. Black lines indicate the impulse response estimates based on admissible structural models satisfying the identification structure. Dashed lines indicate the corresponding pointwise 68% posterior error bands. The errors bands are based on 50 draws from the posterior distribution of the reduced-form parameters with 200,000 rotations each. Oil production refers to the cumulative percent change in oil production.

For example, oil speculators bet on rising prices and they start buying futures contracts. The speculative purchase provides financial incentive for oil companies to buy even more oil and place it in storage causing the real price of oil to rise.

The accumulation of oil stocks might be reinforced by the negative response of the global oil production to a positive financial market shock. This result suggests that oil producers are induced to accumulate inventories in order to sell them at the highest price. Beyond the impact period, the oil futures-spot spread exhibits a sharp reduction followed by a persistent increase in the real price of crude oil. [23]

**Forecast error variance decomposition.** We provide some empirical results of the forecast error variance decomposition (FEVD) [24] of the endogenous variables implied by model 1.1.

In the short run the real price of oil is mainly driven by financial market shocks, accounting for up to 44% of oil price variability. Shocks to precautionary and aggregate demand represent the second and third drivers of oil price fluctuations, with 34% and 17% respectively. Supply shocks have negligible impact on oil price fluctuations, explaining for up to 5%. Interestingly, shocks to the aggregate demand explain up to 39% of oil futures-spot spread fluctuations while precautionary demand shocks contribute up to 15%.

In turn, the explanatory power of shocks to oil supply and financial market represent 15% and 16% of the fluctuations in oil futures-spot spread, respec-

[23]It is important to note that whenever the increases in the oil futures prices are driven by reasons not strictly related to economic fundamentals the arbitrage mechanism can be exploited. The optimal response of the arbitragers is to buy crude oil in the physical market and to sell simultaneously the corresponds amount of futures contracts in the financial market. This strategy is reflected by a contemporaneous increase in the real price of oil and a reduction in the futures prices causing the oil futures-spot spread to decline.

[24]The FEVD allows to quantify the average contribution of a given structural shock to the variability of the data.

tively. These results imply that, on average, shocks to aggregate demand play an important role in explaining the variability of the oil futures spot spread.

**Historical decomposition.** Traditional oil market VAR models include a global proxy for crude oil inventories to capture forward-looking expectations (hence, speculative actions) of oil traders; see among the others Kilian and Murphy (2014); Kilian and Lee (2014); Lombardi and Robays (2011) and Baumeister and Hamilton (2017). Therefore the speculative demand for crude oil reflects a rise in the demand for storage for precautionary purposes or more in general for future consumption. For this investigation we use the definition of oil price speculation as discussed in Fattouh et al. (2013) because in principle both Commercial and Non-Commercial firms [25] could influence the path of the convenience yield.

The authors state that “anyone buying crude oil not for current consumption but for future use” can be considered as a speculator from the economic point of view. The case discussed in Kilian and Murphy (2014) refers to a situation where the inventories' build-up is explained by an increase in the demand for storage. This causes an instantaneous reduction in the oil futures-spot spread which is mainly driven by a rise in the convenience yield. Another possibility is that the accumulation of crude oil inventories causes a contemporaneous increase in the oil futures-spot spread which is mainly explained by a decline in the convenience yield. Therefore the existence of speculative pressure can be identified from changes in the oil futures-spot spread in response to unanticipated financial market shocks. In the last part of this subsection we discuss

[25] The Commodity Futures Trading Commission (CFTC) provides two macro categories for the oil market players: commercial and non-commercial firms. The former include physical participants such as producers, merchants, processors and end-users that have a direct interest in physical oil production, consumption and trade. The latter are mainly made by financial participants like money managers and hedge funds that are interested in trading futures contracts for investment purposes.

the cumulative effect of each shock on the real price of oil, oil futures-spot spread and the global oil production.

Figure 1.3 plots the historical decomposition of the above mentioned three endogenous variables.

During the period 2002-2008, panel (2,1) of figure 1.3 shows that the increase in the real price of oil was mainly triggered by shocks to aggregate demand, most likely driven by global economic growth from OECD countries and emerging Asia. However, the cumulative effect of the aggregate demand shocks decreased between the beginning of 2005 and mid 2006 and rose again until mid-2008. Since 2003 the financial market shocks have contributed significantly to the oil price increase as shown in panel (4,1).

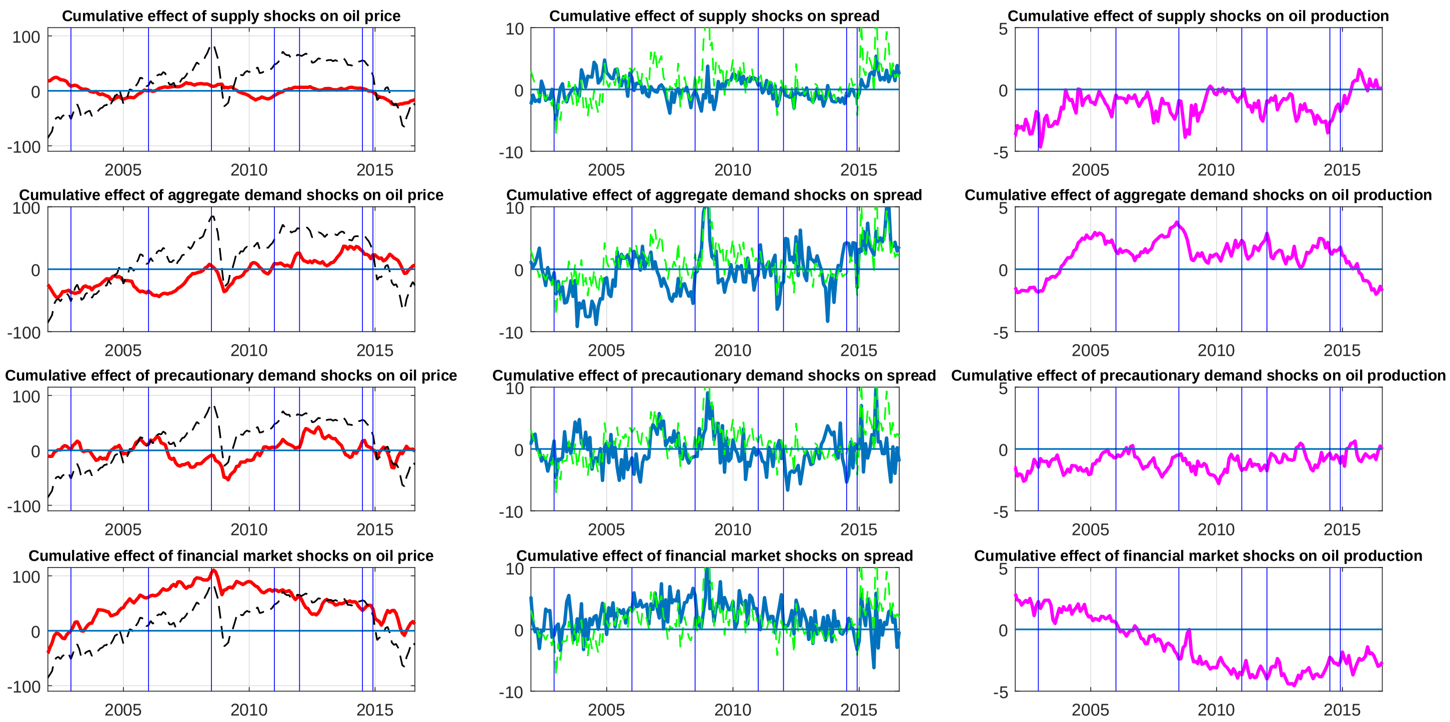
Interestingly, panel (4,2) shows that both rises in the real price of oil and in the oil futures-spot spread were attributed to positive financial market shocks. The latter are likely to reflect a reduction in the convenience yield driven by speculative purchases of futures contracts. Panel (4,3) shows that post-2006, high levels of oil futures-spot spread were associated with a reduction in the global crude oil production, mainly driven by positive financial market shocks. These results might be representative of economic incentives to take oil off the physical market and increase the worldwide oil stocks. [26]

It is important to highlight that panel (3,1) does not provide empirical evidence that the demand for precautionary inventories drove up the real price of oil during the financialization of commodity markets, consistent with the studies of Kilian and Murphy (2014) and Kilian and Lee (2014).

Moreover the surge of the real price of oil during the first six months of 2008

[26] A large fraction of the increase in the global crude oil inventories might be explained by an accumulation of crude oil strategic reserves to protect the economy of emerging countries like China and India against short-term energy crisis.
In the recent period, India continues developing its strategic petroleum reserve, as pointed out by the EIA: `https://www.eia.gov/todayinenergy/detail.php?id=27132`.

Figure 1.3: Historical decompositions based on the SVAR model




*Note:* Black and green dashed lines indicate the observables for real price of oil and oil futures-spot spread, respectively. Solid red line denotes the cumulative effect of each shock on the real price of crude oil. Blue line reflects the cumulative effect of each shock on the oil futures-spot spread. Pink line refers to the cumulative effect of each shock on the worldwide crude oil production. The reference period is 2002:1-2016:7 and vertical lines indicate the major exogenous events in the global market for crude oil: Venezuela crisis in November 2002 followed by the Iraq invasion in early 2003; financialization of commodity markets and great surge of oil price from 2003 until mid 2008; global financial collapse in June 2008; Arab spring between 2011-2012; large drop in oil prices between June and November 2014.

was primary driven by oil demand shocks. In June 2008 the real price of crude oil fell due to the world financial crisis. The main economic reasons behind this drop were explained by negative shocks to precautionary demand for oil in anticipation of the world recession and negative shocks to aggregate demand. By contrast, since August 2008 both the precautionary and the aggregate demand shocks stimulated the recover of the oil prices.

Panel (1,1) shows that in February 2011 there was a small evidence of an increase in the real price of oil associated with the revolution wave in Arab countries.

Finally, the decline in the global price of oil started in November 2014 was mainly driven by a simultaneous combination of the first-three structural shocks. On the supply side, the decline in the price of crude oil might be reflected by the large recovery of oil production from Libya, Syria and Iraq combined with the OPEC's announcement on November 2014 to not reduce the level of crude oil production. Moreover, the OPEC's announcement should also explain a large reduction in the precautionary demand for storage causing the real price of oil to decline and the oil futures-spot spread to increase, as shown in panels (3,1) and (3,2), respectively. Overall, positive supply shocks and a weak demand for crude oil from OECD and emerging countries caused a reduction in the real price of oil during the recent period.

## 1.6 A comparison between SVAR models of the global market for crude oil

This section investigates the main features of SVAR models of the global market for crude oil, reported in table 1.2.
These models are classified according to the types of forward-looking variable (crude oil inventories vs oil futures-spot spread) and the methodology applied to recover the structural shocks. Further details of the identification strategy are reported in appendix 1.9. For each model we provide the economic interpretation of the related identification structure with reference to the implied elasticity of oil demand and oil supply. Moreover, we propose a pairwise comparison of benchmark model ($M_0$) and other specifications that are reported in table 1.2. The comparison is made on the responses of real price of oil and forward-looking variables to each structural shock. Finally we provide a qualitative ranking for the models of interest.

Table 1.2: Alternative SVAR models for global crude oil markets

| **Identification structure** | **Oil futures-spot spread** | **Oil inventories** |
|---|---|---|
| Sign restrictions | $M_0$ | $M_1$ |
| Recursive model | $M_2$ | $M_3$ |
| Non Recursive model | $M_4$ | $M_5$ |

*Note*: $M_0$ refers to the benchmark SVAR model introduced in this analysis. $M_1$ is the model proposed by Kilian and Murphy (2014). $M_2$, $M_3$, $M_4$ and $M_5$ are SVAR models whose structural response estimates are obtained following the Bayesian algorithm proposed by Baumeister and Hamilton (2015). $M_2$ and $M_3$ are recursive models including oil futures-spot spread and crude oil inventories, respectively. $M_4$ is a non-recursive model with oil futures-spot spread. $M_5$ is a 4-variable model with inventories and measurement error discussed in Baumeister and Hamilton (2017)

### 1.6.1 The identification of the structural shocks: an evaluation of different approaches

The first candidate is the model of the global market for crude oil proposed by Kilian and Murphy (2014).

The dataset we use in our empirical work [27] is based on monthly observations which cover the period 1973:2-2009:9. The endogenous variables are (1) the growth rate of monthly crude oil production ($q_t$), the real economic activity index ($rea_t$), the real price of crude oil ($p_t$) and a proxy for global crude oil inventories above the ground ($inv_t$).

The authors recover the structural shocks starting from consistent estimates of the reduced-form VAR model with 24 lags. Then, they impose a specific set of sign and dynamic restrictions on the impulse response functions combined with economic bounds on the impact price elasticity of oil supply and demand.[28]

The relationship between the VAR reduced-form errors ($u_t$) and the structural shocks ($v_t$) is defined as follow:

$$\underbrace{\begin{pmatrix} u_t^q \\ u_t^{rea} \\ u_t^p \\ u_t^{inv} \end{pmatrix}}_{u_t} = \underbrace{\begin{pmatrix} - & + & + & () \\ - & + & - & () \\ + & + & + & () \\ () & () & + & () \end{pmatrix}}_{B_0^{-1}} \underbrace{\begin{pmatrix} v_t^{\text{flow supply shock}} \\ v_t^{\text{aggregate demand shock}} \\ v_t^{\text{speculative demand shock}} \\ v_t^{\text{residual structural shock}} \end{pmatrix}}_{v_t} \quad (1.3)$$

All structural shocks are normalized to obtain an increase in the price of oil on impact. Missing entries mean that no sign restrictions are imposed. For example, an unexpected oil supply disruption causes a drop in the global oil production followed by an instantaneous increase in the real price of oil and a

[27] For this section we use the dataset from Kilian and Murphy (2014), available from the following web-site `http://qed.econ.queensu.ca/jae/2014-v29.3/kilian-murphy/`.

[28] Dynamic restrictions are imposed on the response of global oil production, real economic activity and real price of crude oil to a supply shock.

reduction in the real economic activity. The effect of the shock on the sign of crude oil inventories is ambiguous. This depends on whether crude oil stocks are used for consumption smoothing or precautionary purposes.

An unanticipated positive flow demand shock rises the real economic activity causing the price of oil and the global oil production to increase, on impact. So, even in this case, the effect of the shock on the oil inventories remains ambiguous.

A positive speculative demand shock [29] coincides with an increase in the demand for storage reflected by revision in the forward-looking expectations. The accumulation of crude oil inventories causes global oil production and oil prices to increase whereas the real economic activity to fall, on impact.

Finally, a positive residual shock represents an idiosyncratic innovation which is orthogonal to the previous structural shocks.

It is important to point out that, the baseline specification of our empirical work and the model proposed by Kilian and Murphy (2014) adopt the same methodology to recover the structural shocks.

In particular, the procedure is based on the numerical algorithm discussed in Rubio-Ramirez et al. (2010). This context is suitable for a comparative analysis of the transmission mechanism of oil price shocks. In this respect, several comments can be summarised as follows.

First of all, in $M_1$ an oil supply disruption and a positive speculative supply shock are observationally equivalent. In this case both structural shocks reflect a reduction in the global oil production in anticipation of rising prices.

In general the economic factors behind a flow supply disruption are not related

[29] The speculative demand a' la Kilian and Murphy might reflect different situations such as (1) an expected shortfall of future oil supply relative to future oil demand, (2) an unanticipated shift in uncertainty about future oil disruption and (3) changes in beliefs not strictly related to expected fundamentals. The authors do not consider oil futures prices in their analysis but they exploit the existence of an arbitrage free condition between financial and physical markets.

to speculative reasons. This would imply that a separate transmission channel should be adopted to explain properly oil price speculation, as considered in the identification structure of $M_0$.

Moreover the response of the real economic activity to an oil supply disruption and a positive speculative shock could be different in sign. In other words, negative supply shocks are likely to cause a rise in the price of oil associated with a decline in the economic activity. On the other hand, oil price increases due to speculation activities could not necessary imply a slowdown of the global business cycle. [30]

Another comment that we would like to make concerns the identification in term of sign restrictions. Specifically, the benchmark model proposed in this analysis is fully identified. In contrast, the non-recursive model discussed by Kilian and Murphy (2014) is partially identified. This last issue might complicate the economic interpretation of the residual structural shock.

Finally, another marked difference stems from the boundary restrictions imposed on elements of the impact multiplier matrix in order to generate realistic short-run price elasticity of oil supply.

For consistency, we relax the upper bound restriction on the impact price elasticity of oil supply implied by $M_1$. Thus, we set three times grater the original bound proposed by Kilian and Murphy (2012).

In this study, we show results for $M_1$ with the lowest coefficient of variation for the impact price elasticity of oil supply and with the impact price elasticity of oil demand closest to that reported by $M_0$. Impulse response analysis discussed in section 1.6.3 provides evidence that the following changes do not affect the main results of the original model proposed by Kilian and Murphy

[30] As shown in appendix 1.10, the effect of speculation on oil prices might be described by a simultaneous shifts of oil demand and oil supply curves in the opposite directions rather than a shift to the left of the contemporaneous oil supply curve along the oil demand curve.

(2014).

The second candidate is the recursive model with oil futures-spot spread. We employ monthly data from 1983:3 to 2016:7. The set of observables includes the growth rate of monthly crude oil production ($q_t$), the real economic activity index ($rea_t$), the oil futures-spot spread ($s_t$) and the real price of crude oil ($p_t$). In general, the main feature of the recursive models is that they are exactly identified. This means that there exist a unique impact multiplier matrix ($B_0^{-1}$) capturing the instantaneous relations among the structural parameters given a specific ordering variables of the reduced-form VAR model with 12 lags.
The recursive SVAR model with oil futures-spot spread implies the following relationship between the structural shocks ($v_t$) and the VAR reduced-form errors ($u_t$):

$$\underbrace{\begin{pmatrix} v_t^{\text{oil supply shock}} \\ v_t^{\text{aggregate demand shock}} \\ v_t^{\text{precautionary demand shock}} \\ v_t^{\text{residual structural shock}} \end{pmatrix}}_{v_t} = \underbrace{\begin{pmatrix} 1 & 0 & 0 & 0 \\ -b_{rea,q} & 1 & 0 & 0 \\ -b_{s,q} & -b_{s,rea} & 1 & 0 \\ -b_{p,q} & -b_{p,rea} & -b_{p,s} & 1 \end{pmatrix}}_{B_0} \underbrace{\begin{pmatrix} u_t^q \\ u_t^{rea} \\ u_t^s \\ u_t^p \end{pmatrix}}_{u_t} \tag{1.4}$$

This analysis consists of the specification of informative prior beliefs represented in form of density functions about $B_0$, the lagged structural matrix and the vector collecting the structural disturbances. At this stage we focus only on the elements of the contemporaneous structural matrix $B_0$.
The Bayesian analysis of a recursive model is equivalent to impose a set of zero (or exclusion) restrictions on the elements above the main diagonal of $B_0$ and to put flat (or uninformative) prior distribution for the other parameters.
Thus, for all elements that are not restricted to zero we assign independent *Student t* distribution with location parameter $c_i = 0$, scale $\sigma_i = 100$ and degree of freedom $\nu = 3$, as suggested by Baumeister and Hamilton (2017).

What really matters, is to impose exclusion restrictions economic plausible.
For example, the first row of $B_0$ contains the instantaneous parameters of the oil supply curve. Given the existence of large costs of production typical of the oil industry we postulate that the crude oil supply curve is completely inelastic. As a consequence, the global oil production does not respond to any demand shocks within the same month. This is consistent with the following set of economic restrictions: $b_{q,rea} = b_{q,s} = b_{q,p} = 0$.
The second row of $B_0$ governs the economic activity equation and identifies the aggregate demand shock. This is related to unexpected change in the demand for oil and other industrial commodities mainly driven by the global business cycle.
The recursive structure of matrix $B_0$ implies that global oil production might affect instantaneously the economic activity. On the other hand, the remaining parameters involved in the second equation are set to zero.
The exclusion restriction on $b_{rea,p}$ is consistent with the absence of contemporaneous feedback between the real economic activity index and the price of oil. This is motivated by the fact that ocean carries set fuel charges for single-voyage rates on the basis of the weekly average of each route over the preceding three months, as discussed by Kilian and Zhou (2017). For the same reason we impose the exclusion restriction on the parameter $b_{rea,s}$ of the economic activity equation.
The third row of $B_0$ includes the structural parameters of the oil futures spot spread that are used to identify the precautionary demand shock. A positive shock triggered by precautionary purposes implies an increase in the demand for the above-ground crude oil inventories associated with a rise in the global market value of storage. [31] By construction, there can be no instantaneous

[31] Since the oil futures-spot spread represents a proxy for the market value of storage but expressed with an opposite sign, we expect that a positive precautionary demand shock is

feedback from the price of oil to oil futures-spot spread, implying an exclusion restriction on the coefficient $b_{sp}$. This means that the financial forward looking variable is more related to expectations on future oil market conditions rather than changes in the current spot prices.
It is important to note that, by setting $b_{sp} = 0$, we rule out the role of consumption smoothing for storage and futures markets during high level of oil prices driven by positive residual structural shocks. The latter represent unanticipated changes in the price of oil that cannot be explained by the first three shocks and it is identified by all parameters of the inverse oil demand function, reported in equation 1.4.
Of particular importance for our purposes is the parameter $b_{p,q}$. This represents the reciprocal of the short-run price elasticity of oil demand which is directly inferred from $B_0$.

The third candidate is the recursive model with a proxy for global crude oil inventories above the ground. As described previously, for this analysis we use monthly data from 1983:3 to 2016:7. This model allows for one year' worth of lags and includes a set of endogenous variables ordered as follow: ($q_t$,$rea_t$,$inv_t$,$p_t$). This implies the following relationship between $v_t$ and $u_t$:

$$\underbrace{\begin{pmatrix} v_t^{\text{oil supply shock}} \\ v_t^{\text{aggregate demand shock}} \\ v_t^{\text{precautionary demand shock}} \\ v_t^{\text{residual structural shock}} \end{pmatrix}}_{V_t} = \underbrace{\begin{pmatrix} 1 & 0 & 0 & 0 \\ -b_{rea,q} & 1 & 0 & 0 \\ -b_{inv,q} & -b_{inv,rea} & 1 & 0 \\ -b_{p,q} & -b_{p,rea} & -b_{p,inv} & 1 \end{pmatrix}}_{B_0} \underbrace{\begin{pmatrix} u_t^q \\ u_t^{rea} \\ u_t^{inv} \\ u_t^p \end{pmatrix}}_{u_t} \tag{1.5}$$

We impose a set of six exclusion restrictions on the elements of $B_0$ forming a lower triangular matrix and we assign uninformative prior *Student t* distribution with location parameter $c_i = 0$, scale parameter $\sigma = 100$ and $\nu = 3$

reflected by a decline in the oil futures-spot spread.

degrees of freedom for the remaining structural coefficients.

The main difference from $M_2$ stemming from the type of proxy for the forward-looking expectations of oil traders. In the previous specification, the future crude oil market conditions are inferred from a financial measure (as a proxy for the market price of crude oil-stocks) derived by crude oil futures contracts. In contrast, this model includes a proxy for the above-ground crude oil inventories as widely accepted in the empirical literature on modelling the price of oil. Notwithstanding, the transmission mechanism of the structural shocks are identical in both SVAR models since they are examples of recursive specifications.

Under frequentist inference, in order to retrieve the elements of the impact multiplier matrix, that is $B_0^{-1}$, it is sufficient to apply a Cholesky factorization of the variance covariance matrix of reduced-form errors term. This approach involves a simple identification strategy which is motivated by the economic theory. Therefore, recursive SVAR models are definitely easy to be employed and they provide answers to some interesting questions.

The fourth candidate is the non-recursive model with oil futures-spot spread. For this investigation we use monthly data from 1983:3 to 2016:7. The identification of this model exploits some prior beliefs on the elements of the structural matrix $B_0$. This model allows for one year' worth of lags and includes a set of four endogenous variables, that is: ($q_t$,$rea_t$,$s_t$,$p_t$).

The relationship between the $v_t$ and $u_t$ has the following representation:

$$\underbrace{\begin{pmatrix} u_t^q \\ u_t^{rea} \\ u_t^s \\ u_t^p \end{pmatrix}}_{u_t} = \underbrace{\begin{pmatrix} 1 & 0 & -b_{q,p} & 0 \\ -b_{rea,q} & 1 & -b_{rea,p} & 0 \\ -b_{p,q} & -b_{p,rea} & 1 & -b_{p,s} \\ -b_{p,q} & -b_{p,rea} & -b_{p,p} & 1 \end{pmatrix}}_{B_0} \underbrace{\begin{pmatrix} v_t^{\text{oil supply shock}} \\ v_t^{\text{aggregate demand shock}} \\ v_t^{\text{precautionary demand shock}} \\ v_t^{\text{residual structural shock}} \end{pmatrix}}_{v_t} \tag{1.6}$$

The parameter, $b_{qp}$ denotes the short-run price elasticity of oil supply. For our prior for $b_{qp}$ we assign a *student t* $(c_{qp}, \sigma_{qp}, \nu_{qp})$ distribution, with mode at $c_{qp} = 0.1$, scale parameter $\sigma_{qp} = 0.2$ and degrees of freedom $\nu_{qp} = 3$, truncated to be positive.

Because the Kilian (2009) index of global real economic activity $(rea)$ is derived from bulk dry cargo ocean shipping fright rates we are confident to put a prior distribution for $b_{rea,q}$ with mode at $c_{rea,q} = 0$, scale parameter $\sigma_{rea,q} = 0.1$ and degrees of freedom $\nu_{rea,q} = 3$. This implies the absence of feedback between changes in the amount of crude oil and the real economic activity index.

Recently, the Kilian's index exhibited some erratic behaviour that is hard to square with smooth fluctuations in the global business cycle.

A potential bias might arise because of the dependence between the bulk dry cargo rates and the price of crude oil. The validity of this economic conjecture can be easily tested under Bayesian framework.

For this reason, we represent the effect of oil prices on the real economic activity index with a very uninformative *student t* $(c_{rea,p}, \sigma_{rea,p}, \nu_{rea,p})$ prior distribution for $b_{rea,p}$ with mode at $c_{rea,p} = 0$, scale parameter $\sigma_{rea,p} = 100$, degrees of freedom $\nu_{rea,p} = 3$ and truncated to be negative. The resulting truncation should reflect the economic beliefs that an increase in the cost of bunker fuel causes a reduction in the volume of shipping in the commodity markets and hence in the $rea$ variable.

The parameter $b_{qp}$ represents the reciprocal of the short run price elasticity of oil demand. Consistent with the empirical literature on estimating the price elasticity of oil demand we put a *student* $t(c_{pq}, \sigma_{pq}, \nu_{pq})$ prior distribution with mode at $c_{31} = -5$, scale parameter $\sigma_{31} = 0.2$ , degrees of freedom $\nu_{31} = 3$ and truncated to be negative. Our prior density for $b_{qp}$ implies a short-run demand elasticity centred around 0.2 in the absolute value.

The parameter $b_{p,rea}$ denotes the effect of changes in economic activity (measured by *rea* index) on the price of crude oil. Since we do not have a direct measure of industrial production we are only able to postulate a positive feedback from real economic activity to the price of oil. Therefore we put a relative uninformative *student* $t(c_{p,rea}, \sigma_{p,rea}, \nu_{p,rea})$ prior distribution with mode at $c_{p,rea} = 0$, scale parameter $\sigma_{p,rea} = 0.5$, degrees of freedom $\nu_{p,rea} = 3$ and truncated to be positive.
Finally, for the parameters of the oil futures-spot spread equation we assign completely uninformative prior *student* $t$ distribution, with location parameter $c_i = 0$, scale $\sigma_i = 0.5$ and degrees of freedom $\nu = 3$.
The identification structure implies also three exclusion restrictions. The first-two involve the elements of the structural oil supply equation and they postulate that $b_{q,rea} = b_{q,s} = 0$. The last exclusion restriction implies that the real economic activity is not directly affected by the oil futures-spot spread, that is $b_{rea,s} = 0$.

The last candidate is the 4-variable model with inventories and measurement error as proposed by Baumeister and Hamilton (2017).
The set of aggregate variables includes monthly data on global crude oil production, economic activity, real price of oil and inventories. The authors replace the proxy for the real economic activity proposed by Kilian (2009) with a direct measure of world industrial production index ($WIP$). This variable is based on the OECD and six majors other countries' as constructed in Baumeister and Kilian (2016). The following indicator allows to exploit more precisely information about the income elasticity of oil demand.
Moreover $M_5$ includes the WTI spot price in order to increase the size of the dataset and use observation from an earlier sample (1958:1-1975:1) to further inform the prior of the real price of oil. The latter is based on the US refiner's

imported acquisition cost.

Analogous to the previous models, even in this case the identification structure implies a set of priors distribution for the elements of the matrix $B_0$ which is designed to capture the structural relation among the endogenous variables. In addition the Bayesian procedure accounts for the presence of measurement errors which might arise from the inclusion of the OECD crude oil data as a proxy for the global crude oil inventories.

For further details about the identification scheme of $M_5$ the reader is referred to Baumeister and Hamilton (2017).

### 1.6.2 Measuring the global price elasticities of oil demand and oil supply

The short-run price supply and demand elasticity plays a crucial role in determining the contribution of each structural shock on the global price of crude oil.

According to Hamilton (2009a) the cost of refined products are about twice the price of crude oil. This conjecture suggests a value for the global price elasticity of oil demand larger than what implied by the US price elasticity of gasoline demand.

Table 1.3 reports some estimates of own-price elasticities of U.S. household demand for gasoline, distinguishing between short-long horizons and single-systems equation models.

Traditional studies on estimating the short-run price gasoline demand elasticity are based on single-equation estimation.

In this context, conventional OLS methodology is wrong because model violates the orthogonality conditions between predictors and errors term. This yields with biased response of gasoline consumption (production) to changes

Table 1.3: Benchmark elasticities

| **Price demand elasticity** | | |
|---|---|---|
| *Long-run estimate* | *Methodology* | *Study* |
| -0.81 | Cross-sectional analysis | Hausman and Newey (1995) |
| -0.9 | Cross-sectional analysis | Yatchew and No (2001) |
| -0.86 | Survey | Dahl and Sterner (1991) |
| -0.58 | Meta-analysis | Espey (1998) |
| -0.77 | Survey | Graham and Glaister (2003) |
| -0.84 | Meta-analysis | Brons et al. (2008) |
| *Short-run estimate* | *Methodology* | *Study* |
| | *Single equations* | |
| -0.26 | Survey | Dahl and Sterner (1991) |
| -0.07 | Cross-section analysis | Hughes et al. (2008) |
| -0.22 | Panel data analysis | Gelman et al. (2016) |
| -0.37 | Panel data analysis | Coglianese et al. (2017) |
| -0.35 | Simulation analysis | Bento et al. (2009) |
| -1.14 | Panel-data and time-series analysis | Davis and Kilian (2011) |
| | *System of equations* | |
| -0.60 | Panel data analysis | Nicol (2003) |
| -0.70 | Panel data analysis | Oladosu (2003) |
| -0.46 | Panel data analysis | West and Williams (2004) |
| -0.75 | Panel data analysis | West and Williams (2007) |
| -0.50 | Cross-sectional analysis | Tiezzi and Verde (2014) |
| **Price supply elasticity** | | |
| *Estimate* | *Methodology* | *Study* |
| 0.0258 | Historical experience | Kilian and Murphy (2012) |
| 0.11 | Panel data analysis | Caldara et al. (2017) |

in gasoline price. [32]

A natural solution of the endogenity problem is the use of instrumental variable for gasoline price. As pointed out by Coglianese et al. (2017), the choice of a proper instrument, that is correlated with the price of oil and uncorrelated with shocks to demand or supply is not trivial.

An analysis by Hughes et al. (2008) point out that, empirical results of Dahl and Sterner (1991) who use prices of refinery products to instrument gasoline

[32] The simultaneity bias arises when the dependent variable, consumption or production, is jointly determined with the explanatory variable, price of gasoline, typically through an equilibrium mechanism.

prices are misleading. The reason is that, prices of refinery products do not represent accurate instruments because they are positively correlated with the price of gasoline but also affected by gasoline demand shocks. To deal with this issue, Hughes et al. (2008) propose to instrument the price of gasoline with changes in global crude oil production occurring in Venezuela due to the oil strike workers. A study by Davis and Kilian (2011) use the changes in gasoline taxes as a strong and exogenous instrument of gasoline price. They find out that in the short run the estimate of price elasticity of gasoline demand is -1.14, a puzzling high value.

Coglianese et al. (2017) show that retail consumers and gasoline station operators anticipate the effect of taxes on gasoline prices increasing the gasoline purchase during the period immediately before the implementation of taxation. As a consequence the gasoline tax is not exogenous.

To overcome this issue, Coglianese et al. (2017) propose to instrument the gasoline prices by including one lead before the tax hikes and one lag in the month of the tax increase. The following lag-specification allows to control for unconventional higher and lower expected purchases, respectively.

In related work, Caldara et al. (2017) propose to use exogenous drops in oil consumption occurred in other countries as instrumental variables for oil prices. The idea is that, changes in price of oil explained by other countries are independent from changes in amount of consumption or production related to the country of interest. Some examples of exogenous shocks discussed in their analysis refer to geopolitical events, political unrest and earthquake or hurricanes.

In this way, the authors obtain estimates of short-run price demand (supply) elasticity by regressing consumption (production) in each country against the fitted price obtained from the first stage regression. The price supply and demand elasticity resulting from the following estimation is 0.07 and -0.07, respectively. These values represent the elasticities target that are used as external information to solve the identification problem in the SVAR framework. In particular, their strategy selects a pair of admissible elasticities by minimizing the Euclidean distance between the target elasticities and the VAR-admissible elasticities. The resulting median global crude oil supply and demand elasticities are 0.11 and -0.13, respectively.

Interestingly, global elasticities estimated from system of equations are higher than the elasticity obtained by using a single linear approach, consistent with the narrative in Tiezzi and Verde (2014) and Coglianese et al. (2017).

For our purposes, we should focus on the values referring to a system-based estimate because in principle single equation models tend to find lower price elasticities (in absolute value) than those works including system endogenous models.

This finding is consistent with early studies by Nicol (2003); Oladosu (2003); West and Williams (2004) and more recent works by West and Williams (2007); Tiezzi and Verde (2014); Kilian and Murphy (2014). Tables 1.4 and 1.5 show values of the global price demand and supply elasticity implied by each model reported in table 1.2.

In this analysis, we distinguish between the elasticity estimates inferred from the parameters of the structural equations, embodied in $B_0$, and those obtained from the impact multiplier matrix $B_0^{-1}$. The latter represents the reference approach for our discussion since the elasticity implied by $B_0^{-1}$ is available for all models.

As pointed out by Kilian and Murphy (2014), the identification of the demand elasticity requires an exogenous shift of the contemporaneous supply curve along the contemporaneous demand curve, within the context of a struc-

Table 1.4: Elasticity of global oil demand

**Short-run global price demand elasticity**

| | Structural matrix $B_0$ | | |
|---|---|---|---|
| | Elasticity | | |
| SVAR models | $50^{th}$perc | $16^{th}$perc. | $84^{th}$perc. |
| Benchmark model ($M_0$) | n.a | n.a | n.a |
| Sign restriction model ($M_1$) | n.a | n.a | n.a |
| Recursive model ($M_2$) | -1.36 | -2.23 | -0.97 |
| Recursive model ($M_3$) | -1.18 | -1.85 | -0.86 |
| Non-recursive model ($M_4$) | -0.20 | -0.21 | -0.19 |
| Non-recursive model ($M_5$) | -0.35 | -0.51 | -0.24 |

| | Impact multiplier matrix $B_0^{-1}$ | | | |
|---|---|---|---|---|
| | Elasticity in use | Elasticity in production | | |
| SVAR models | Estimate | Estimate | $16^{th}$perc. | $84^{th}$perc. |
| Benchmark model ($M_0$) | n.a | -0.54 | -0.13 | -0.75 |
| Sign restriction model ($M_1$) | -0.35 | -0.46 | -0.37 | -1.20 |
| Recursive model ($M_2$) | n.a | -1.63 | -1.03 | -3.52 |
| Recursive model ($M_3$) | n.a | -1.14 | -0.81 | -1.85 |
| Non-recursive model ($M_4$) | n.a | -0.79 | -0.51 | -1.29 |
| Non-recursive model ($M_5$) | n.a | -0.46 | -0.35 | -0.59 |

tural model.[33]

As a result, we can interpret the ratio between the impact responses of global oil production and real price of oil to an oil supply disruption, as the short-run price global demand elasticity. This is also denoted by oil demand elasticity in production, consistent with the narrative in Kilian and Murphy (2014).

Moreover, the authors propose an alternative measure of elasticity, accounting for the role of inventories in smoothing oil consumption. The latter is called oil demand elasticity in use. Notice that, to get an estimate of price demand elasticity in use we need to include the proxy for global crude oil inventories in the set of endogenous variables. For this reason, this analysis focuses on the price demand elasticity in production.

[33] Analogous reasoning is for the supply elasticity. Specifically, the supply elasticity requires an exogenous shift of the contemporaneous demand curve along the contemporaneous supply curve. Since we disentangle the demand for crude oil in three economic different ways, we yield three different values for the elasticity of oil supply.

Table 1.5: Elasticity of global oil supply

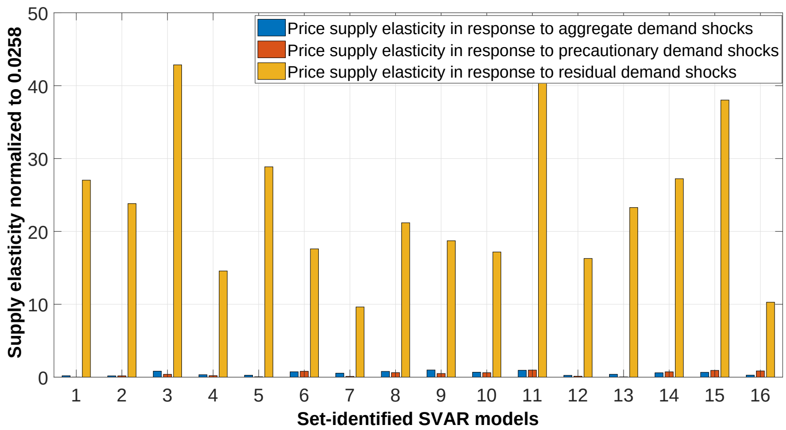
| **Short-run global price supply elasticity** | | | |
|---|---|---|---|
| Elasticity based on structural matrix $B_0$ | | | |
| SVAR models | $50^{th}$percentile | $16^{th}$percentile | $84^{th}$percentile |
| Benchmark model ($M_0$) | n.a | n.a | n.a |
| Sign restriction model ($M_1$) | n.a | n.a | n.a |
| Recursive model ($M_2$) | 0 | 0 | 0 |
| Recursive model ($M_3$) | 0 | 0 | 0 |
| Non-recursive model ($M_4$) | 0.02 | 0.02 | 0.03 |
| Non-recursive model ($M_5$) | 0.15 | 0.09 | 0.22 |
| Elasticity based on impact multiplier matrix $B_0^{-1}$, in response to | | | |
| *Aggregate demand shock* | | | |
| SVAR models | Estimate | $16^{th}$percentile | $84^{th}$percentile |
| Benchmark model ($M_0$) | 0.06 | 0.02 | 0.05 |
| Sign restriction model ($M_1$) | 0.01 | 0.02 | 0.07 |
| Recursive model ($M_2$) | 0 | 0 | 0 |
| Recursive model ($M_3$) | 0 | 0 | 0 |
| Non-recursive model ($M_4$) | 0.02 | 0.01 | 0.02 |
| Non-recursive model ($M_5$) | 0.12 | 0.10 | 0.13 |
| *Precautionary demand shock* | | | |
| SVAR models | Estimate | $16^{th}$percentile | $84^{th}$percentile |
| Benchmark model ($M_0$) | 0.07 | 0.04 | 0.07 |
| Sign restriction model ($M_1$) | 0.02 | 0.02 | 0.07 |
| Recursive model ($M_2$) | 0 | 0 | 0 |
| Recursive model ($M_3$) | 0 | 0 | 0 |
| Non-recursive model ($M_4$) | 0.02 | 0.01 | 0.03 |
| Non-recursive model ($M_5$) | 0.11 | 0.09 | 0.15 |
| *Residual demand shock* | | | |
| SVAR models | Estimate | $16^{th}$percentile | $84^{th}$percentile |
| Benchmark model ($M_0$) | -0.06 | -0.81 | 0.04 |
| Sign restriction model ($M_1$) | 0.27 | 1.54 | 1.58 |
| Recursive model ($M_2$) | 0 | 0 | 0 |
| Recursive model ($M_3$) | 0 | 0 | 0 |
| Non-recursive model ($M_4$) | 0.02 | 0.01 | 0.03 |
| Non-recursive model ($M_5$) | 0.12 | 0.09 | 0.14 |

The resulting estimates of oil supply and oil demand elasticity for the benchmark model are in absolute value 0.06 and 0.54, respectively. These estimates are consistent with analogous studies reported in table 1.3.

Figure 1.4 depicts the impact price elasticity of oil supply normalized to 0.0258, for the set identified model discussed in Kilian and Murphy (2014), under its original identification. We highlight that, the numerical values of this ratio associated with aggregate and precautionary demand shocks are less than one. Conversely, the normalized price supply elasticity in response to residual demand shocks can be larger than its postulated value, depending on the structural model of interest.

For some models, the price supply elasticity in response to a positive residual demand shock is 40 times larger than what originally imposed. This result casts doubts on the accuracy of price supply elasticity. Therefore, in this analysis we impose an upper bound restriction on the ratio between the impact responses of oil production and real price of oil to residual demand shocks.

Figure 1.4: Kilian and Murphy (2014)'s set identified model

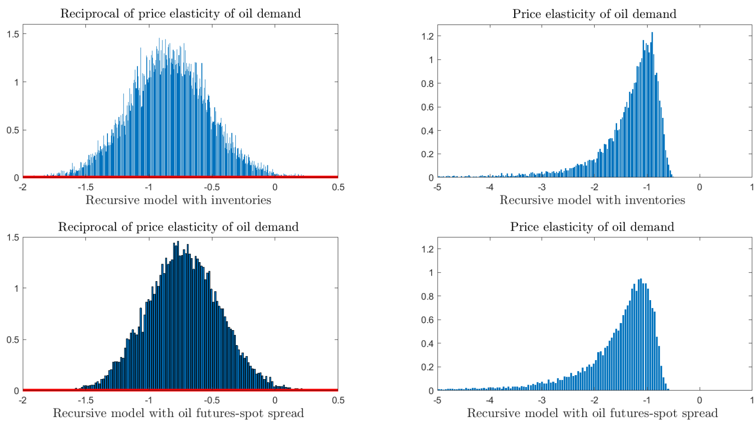



*Note*: Following the original identification strategy discussed in Kilian and Murphy (2014) we obtain a set of 16 structural models conditional on the least squares estimate of the reduced-form. The authors focus on model number six. This model yields an impact price elasticity of oil demand in use closest to the posterior median of this elasticity among the candidate models that satisfy all identifying restrictions.

Caldara et al. (2017) prove the existence of an inverse and non-linear relation between oil demand and oil supply elasticity. In some cases, the empirical relation provides economically implausible estimates of short-run price supply and demand elasticities. This analysis offers supporting evidence in this regard, especially for recursive models.

One might ask what the consequences of Cholesky identification on the economic results might be, given the simplicity of this traditional approach. We

Figure 1.5: The implied global oil demand elasticity for recursive SVAR models




*Note*: Baseline prior (solid red curve) and posterior (blue histograms) distributions concerning $b_{q,p}$ and the impact price elasticity of oil demand.

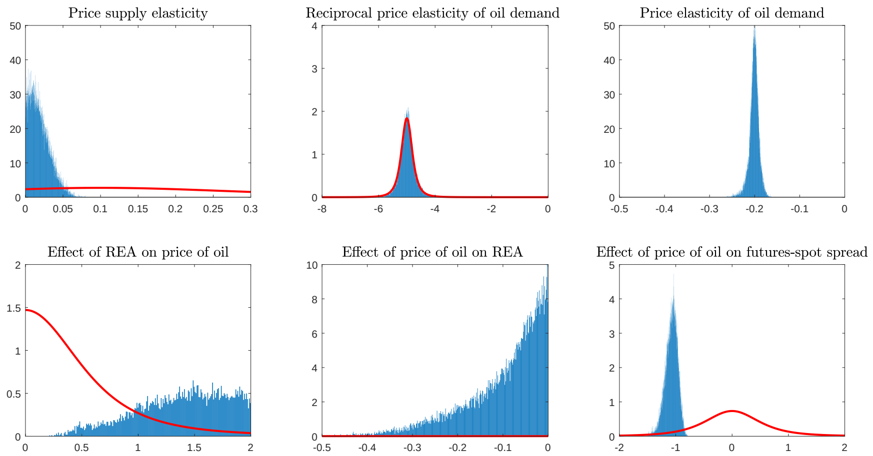
have two comments to make on this. First, zero-restrictions might represent too strong assumptions in the real world. Second, recursive oil market VAR models might induce implausible values for the short-run price demand elasticity.

As regards the last point, Baumeister and Hamilton (2017) provide evidence that the SVAR model discussed in Kilian (2009) implies a very elastic values for the oil demand elasticity. They show that the posterior distribution of the reciprocal of the price elasticity of oil demand is concentrated between -0.6 and +0.2. This means that the demand function implied by model discussed in Kilian (2009) is not only very elastic but it can be also upward-sloping.

In sum, the dynamic responses of the endogenous variables to each structural shock for recursive models might be misleading.

This issue can be easily overcome by adopting an identification scheme based on sign restrictions that allows to restrict the impact price elasticity of oil demand to be negative. However, in this analysis we show that, by including the forward-looking measure as third variable in the recursive SVAR model, the probability of observing $b_{qp} > 0$ falls dramatically.

Figure 1.6: Prior against posterior distribution of some elements of $B_0$ for model with oil futures-spot spread ($M_4$)




*Note*: Baseline prior (solid red curve) and posterior (blue histograms) distributions concerning the structural parameters for model $M_4$.

Figure 1.5 shows that, in both models the posterior distribution for $b_{q,p}$ has most of its mass for negative values. Our result provides evidence that the dynamic responses of recursive oil market SVAR models imply economic plausible sign for the oil demand elasticity. However, the underlying models lead us to conclude that the crude oil demand is extremely elastic in response to unexpected changes in the price of oil.

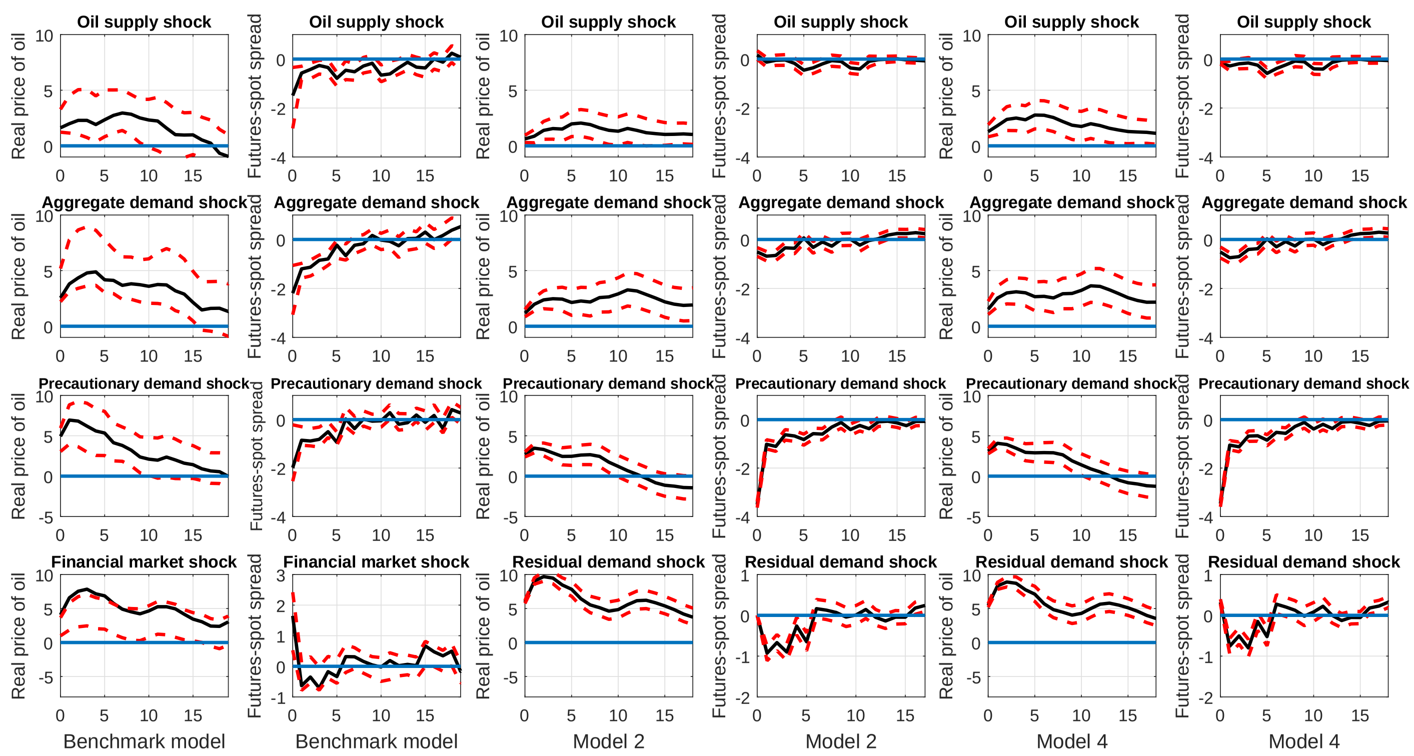
Figure 1.6 plots both the prior and posterior distribution for some of the structural elements of model $M_4$. Four basic features emerge. First, the posterior median of the short-run price elasticity of oil supply, $b_{q,p}$ is 0.024. The value is smaller than the estimate reported by Baumeister and Hamilton (2017) but it is consistent with the results of Kilian and Murphy (2014). Second, our prior beliefs about the short-run price elasticity of oil demand is economically plausible. This is confirmed by the posterior median of $b_{p,q}$ which is -0.20, a value in accordance with other empirical results. Third, most of the probability mass for $b_{p,rea}$ is from 1.2 to 2. This is consistent with the result of Kilian and Murphy (2012), who find that the effects of real economic activity on the price of oil is not zero (as postulated by Kilian (2009)) but equals to 2.2. Finally, the posterior distribution for $b_{rea,p}$ provides empirical evidence of the absence of direct feedback from bunker fuel price to the real economic activity index.

### 1.6.3 A comparison based on the impulse responses of price of oil and forward-looking variables to each structural shock

The aim of this subsection is to compare the impulse responses of the real price of oil and the forward-looking variables between $M_0$ and the alternative models reported in table 1.2.
It is important to note that the economic meaning of the first-three structural shocks and their effect on the variables of interest should be similar across models. Figures 1.7 and 1.8 depict the impulse responses of real price of oil and forward-looking variables for each model discussed in this analysis. [34]
The impact price responses to the first-three structural shocks implied by $M_0$ are qualitatively similar both in terms of shape and magnitude to those reported by $M_1$. The main difference between $M_0$ and $M_1$ is the impulse response of the price of oil to residual structural shocks. In model $M_1$, a positive residual structural shock causes an instantaneous rise in the demand for storage followed by a reduction in the real price of oil. According to Kilian and Murphy (2014) the economic meaning and the transmission mechanism of the residual structural shock is not simple to figure out.
The pairwise comparison of $M_0$ and $M_2$ reported in figure 1.7 should be dis-

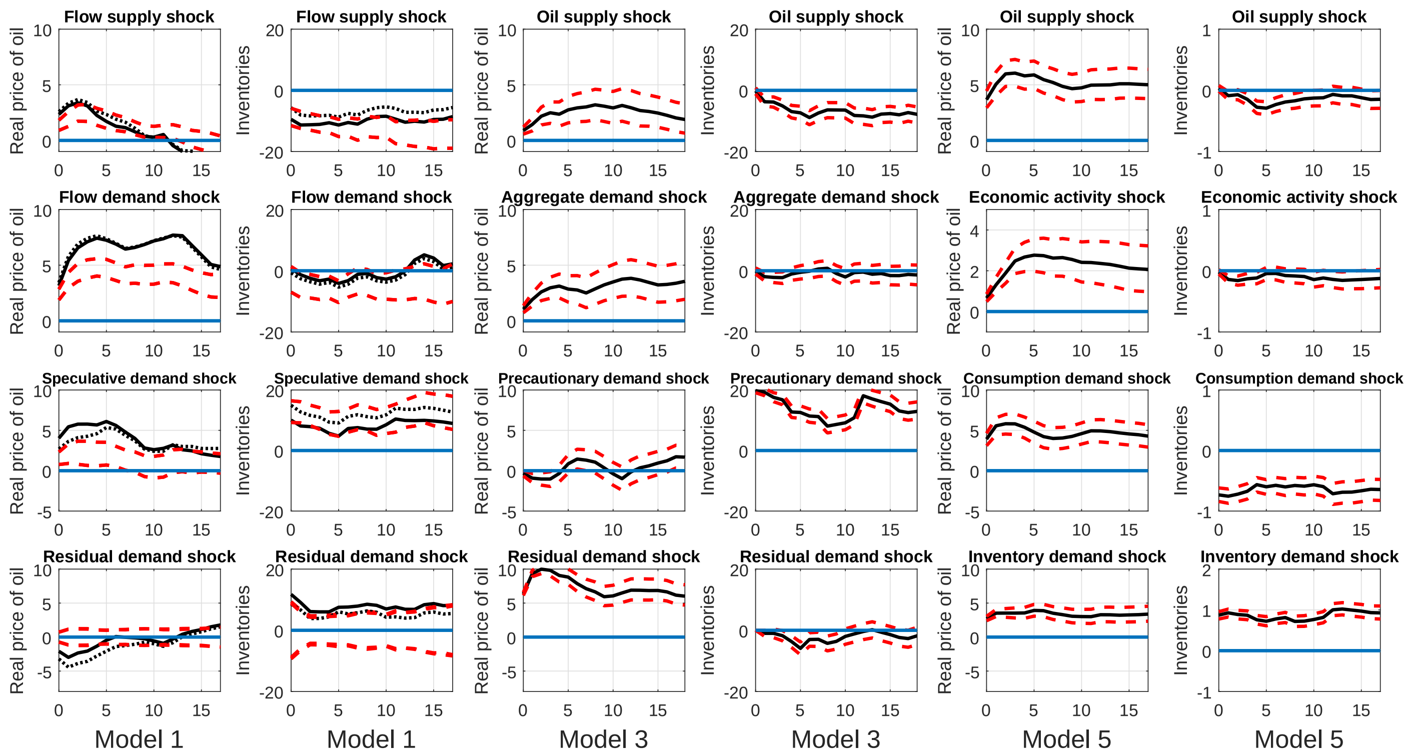
[34] As regards $M_1$, dotted black line is the impulse response estimate of the real price of oil under the original specification by Kilian and Murphy (2014). While solid black line denotes the impulse response estimate of the real price of oil under the revised identification of the Kilian and Murphy's model as discussed in section 1.6.1.

Figure 1.7: Impulse response estimates of real price of oil and futures-spot spread.




*Note:* Solid black lines indicate the price responses to one-standard deviation structural shocks for all SVAR models. The impulse response estimates constructed from Baumeister and Hamilton (2015) refer to the Bayesian posterior median. Dashed red lines indicate the corresponding pointwise 68% posterior error bands. .

Figure 1.8: Impulse response estimates of real price of oil and inventories.




*Note:* Solid black lines indicate the price responses to one-standard deviation structural shocks for all SVAR models. The impulse response estimates constructed from Baumeister and Hamilton (2015) refer to the Bayesian posterior median. Dashed red lines indicate the corresponding pointwise 68% posterior error bands. Dashed black line refers to the impulse price response estimates based on the original set of identification proposed by Kilian and Murphy (2014).

cussed with caution since the models provide two different estimates of their oil demand elasticity. For the benchmark model the impact price elasticity of oil demand is 0.54 in absolute value which is consistent with the results of Serletis et al. (2010); Guerrieri and Bodenstein (2012); Baumeister and Peersman (2013) and Kilian and Murphy (2014).

Conversely, the median of the posterior distribution of the price elasticity of oil demand implied by $M_2$ is around -1.36 which is not truly representative of the global market for crude oil. The benchmark model implies somewhat larger impact responses of the price of oil to oil supply disruptions and positive aggregate demand shocks. This is not surprising given their differences in term of short-run price elasticities of oil demand. Positive precautionary demand shocks have similar effects on the magnitude of the price of oil.

Finally the residual structural shocks of $M_0$ and $M_2$ do not reflect the same economic interpretation providing different empirical impact estimates of the real price of oil.

Figure 1.8 shows the impulse responses function of recursive model with crude oil inventories ($M_3$). In particular, an oil supply disruption and a positive shock to aggregate demand causes an instantaneous increase in the real price of oil, as grounded on the theory. On the other hand, a positive precautionary demand shock causes an increase in the level of inventories followed by a contemporaneous decline in the price of oil. This is clearly at odds with the economic theory.

The pairwise comparison of $M_0$ and $M_4$ reported in figure 1.7 exhibit striking qualitative similarities with the responses of oil price and the oil futures-spot spread to each structural shock.

Finally the pairwise comparison of $M_0$ and $M_5$ shows that both models produce similarly price response estimates to positive aggregate and precautionary demand shocks. Analogous results hold in case of positive shocks to financial and inventory markets. As a consequence both structural shocks cause the real price of oil to rise.

In the end, the models in question provide qualitatively similar impact price responses to each structural shock confirming their accuracy to describe properly the effect of residual structural shock on the real price of crude oil.

### 1.6.4 A qualitative rank of SVAR models for global crude oil markets

In this subsection we provide a qualitative method to rank oil market VAR models on the basis of their impulse response functions. In the first place, we need an objective criterion defining rules for the evaluation of all impact responses. The criterion discussed in this work consists of four main points.

First, the impulse responses function have to imply plausible values of oil supply and oil demand elasticities.

Second, the sign of the impact responses need to follow the economic theory.

Third, for a generic $i, j$ impact response denoted by $B^{-1}_{0_{(ij)}}$, we prefer $B^{-1}_{0_{(ij)}} \neq 0$ than $B^{-1}_{0_{(ij)}} = 0$. The latter arises due to exclusion restrictions imposed on the elements of the structural matrix. In general, researchers aim to relax zero restrictions because they are based on strong assumptions for the global crude oil markets.

Fourth, if an impact response is grounded on the theory and its credible region (CR) excludes zero as a possible outcome then it be highly rated. On the other hand, if an impact response is an odds with its theoretical framework and it excludes the zero-value in the corresponding credible set then it will be lower rated. It is important to highlight that the ordering of these four points matters for the final rank. Table 1.6 shows the evaluation criterion with the

Table 1.6: Evaluation criterion for the impact responses

| Rating for $B^{-1}_{0_{(ij)}}$ | Outcomes for $B^{-1}_{0_{(ij)}}$ | | | Rank | Score |
|---|---|---|---|---|---|
| A | Economic theory | $B^{-1}_{0_{(ij)}} \notin 0$ | $0 \notin$ CR | $1^{st}$ | 5 |
| B | Economic theory | $B^{-1}_{0_{(ij)}} \notin 0$ | $0 \in$ CR | $2^{nd}$ | 4 |
| C | Economic theory | $B^{-1}_{0_{(ij)}} \in 0$ | $0 \in$ CR | $3^{rd}$ | 3 |
| D | Non-economic theory | $B^{-1}_{0_{(ij)}} \notin 0$ | $0 \in$ CR | $4^{th}$ | 2 |
| E | Non-economic theory | $B^{-1}_{0_{(ij)}} \notin 0$ | $0 \notin$ CR | $5^{th}$ | 1 |

*Note:* In table 1.6 there are five different types of rating with their associated scores.

Table 1.7: The economic sign of the impact responses

| Variables | I shock | II shock | III shock | IV shock |
|---|---|---|---|---|
| Oil production | - | + | + | () |
| Economic activity | - | + | - | () |
| Price of oil | + | + | + | () |
| *Forward-looking variables:* | | | | |
| Inventories | - | - | + | () |
| Oil futures-spot spread | - | - | - | () |

*Note:* The SVAR models identify four structural shocks. The first shock (I) is a negative oil supply shock. The second (II) is a positive shock to aggregate demand. The third shock (III) represents a positive precautionary demand shock. The fourth shock is a positive residual (or idiosyncratic) structural shock (IV) whose meaning is strictly related to the specific model.

relative scores for the impact responses of the SVAR models covered in this analysis.[35] The economic theory is summarized in table 1.7 and it reports the expected outcomes on the elements of the impact multiplier matrix, in accordance with empirical works proposed in this field.

For example, let us suppose that we are interested in assessing the accuracy of the impact response of the crude oil inventory to the first structural shock. It is widely accepted that a negative supply shock causes an instantaneous reduction in the global oil production, economic activity and a rise in the real price of oil. Therefore the role of storage for consumption smoothing will imply

[35] The fourth shock is a positive idiosyncratic structural shock whose meaning is strictly related to the specific model. For this reason we are not able to provide a common sign of the impact response of the endogenous variables to residual demand shocks.

Table 1.8: Ranking of the impact responses

| **SVAR models** | **I structural shock** | | | | | | **II structural shock** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | A | B | C | D | E | Rank | A | B | C | D | E | Rank |
| $M_0$ | 4 | 0 | 0 | 0 | 0 | $1^{st}$ | 4 | 0 | 0 | 0 | 0 | $1^{st}$ |
| $M_1$ | 4 | 0 | 0 | 0 | 0 | $1^{st}$ | 3 | 1 | 0 | 0 | 0 | $3^{rd}$ |
| $M_2$ | 2 | 0 | 0 | 2 | 0 | $6^{th}$ | 3 | 0 | 1 | 0 | 0 | $5^{th}$ |
| $M_3$ | 2 | 1 | 0 | 1 | 0 | $5^{th}$ | 2 | 1 | 1 | 0 | 0 | $4^{th}$ |
| $M_4$ | 3 | 1 | 0 | 0 | 0 | $3^{rd}$ | 4 | 0 | 0 | 0 | 0 | $1^{st}$ |
| $M_5$ | 3 | 0 | 0 | 1 | 0 | $4^{th}$ | 3 | 0 | 0 | 1 | 0 | $6^{st}$ |
| **Total Responses** | **18** | **2** | **0** | **4** | **0** | | **19** | **2** | **2** | **1** | **0** | |

| **SVAR models** | **III structural shock** | | | | | | **IV structural shock** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | A | B | C | D | E | Rank | A | B | C | D | E | Rank |
| $M_0$ | 4 | 0 | 0 | 0 | 0 | $1^{st}$ | 2 | 2 | 0 | 0 | 0 | $3^{rd}$ |
| $M_1$ | 4 | 0 | 0 | 0 | 0 | $1^{st}$ | 0 | 4 | 0 | 0 | 0 | $4^{th}$ |
| $M_2$ | 2 | 0 | 2 | 0 | 0 | $4^{th}$ | 1 | 0 | 3 | 0 | 0 | $6^{th}$ |
| $M_3$ | 1 | 0 | 2 | 1 | 0 | $5^{th}$ | 1 | 0 | 3 | 0 | 0 | $6^{th}$ |
| $M_4$ | 4 | 0 | 0 | 0 | 0 | $1^{st}$ | 4 | 0 | 0 | 0 | 0 | $1^{st}$ |
| $M_5$ | 2 | 1 | 0 | 0 | 1 | $6^{th}$ | 4 | 0 | 0 | 0 | 0 | $1^{st}$ |
| **Total Responses** | **17** | **1** | **4** | **1** | **1** | | **12** | **6** | **6** | **0** | **0** | |

| **SVAR models** | **All structural shocks** | | | | | | |
|---|---|---|---|---|---|---|---|
| | A | B | C | D | E | Score | Rank |
| $M_0$ | 14 | 2 | 0 | 0 | 0 | 78/80 | $2^{nd}$ |
| $M_1$ | 11 | 5 | 0 | 0 | 0 | 75/80 | $3^{rd}$ |
| $M_2$ | 8 | 0 | 6 | 2 | 0 | 62/80 | $5^{th}$ |
| $M_3$ | 6 | 2 | 6 | 2 | 0 | 60/80 | $6^{th}$ |
| $M_4$ | 15 | 1 | 0 | 0 | 0 | 79/80 | $1^{st}$ |
| $M_5$ | 12 | 1 | 0 | 2 | 1 | 69/80 | $4^{th}$ |
| **Total Responses** | **66** | **11** | **12** | **6** | **1** | | |

a reduction in the level of crude oil inventories, irrespective the methodology employed to solve the identification problem.

In the beginning, for every model we assign a score of each impulse response estimate in order to provide a provisional ranking.

Tables 1.8 reports the absolute frequencies of the rating assigned to each impact response. Since we have six oil market VAR models and four structural shocks overall we evaluate ninety-six impulse response estimates.

The instantaneous effect of the first structural shock (oil supply shock) on the endogenous variables are properly explained by non-recursive models, especially for those with identification scheme based on sign restrictions on the elements of the impact multiplier matrix.

As regards the recursive models, an oil supply disruption represents the only structural shock that can be transmitted without imposing zero restrictions on the set of endogenous variables.

Moreover, recursive models including oil futures-spot spread and crude oil inventories as forward-looking variables have an half and a quarter of their impact responses in rating D, respectively. Overall, 75% and 8% of the impact responses of an oil supply shock to all variables are rated A and B respectively, while the remaining responses are rated D.

The contemporaneous effect of the second structural shock (aggregate demand shock) on the endogenous variables is very clearly explained by all models discussed in this analysis. Overall, 80% of the impact responses of each variable are rated A, 4% B and the remaining 8% respectively C and D. Neither of the impact responses are rated E.

The impact responses of all endogenous variables to the third structural shock (precautionary demand for crude oil) are very accurate for non-recursive models, except for the model proposed by Baumeister and Hamilton (2017). The latter have some limits in explaining properly the effects of shocks, specific to oil markets, on the set of endogenous variables.

In particular, the impact response of crude oil inventories to positive precautionary demand shocks is negative. This represents the lowest rating among all models discussed in this analysis. As regards the effects of residual structural shocks, non-recursive models, with identification strategy based on prior density functions on the elements of the structural matrix $B_0$, provide very accurate impact responses (100% rated A). In sum, 50% of the impact responses of each variable are rated A, and the remaining equal shares are rated B and C. The final ranking for the assessment of the impact responses is reported

Table 1.9: Ranking SVAR models

| **SVAR models** | **Supply elasticity** *Estimate* | 0 | $\neq 0$ | **Short-run demand elasticity** *Estimate* | $(0; 0.6)$ | $[0.6; 1)$ | $[1; +\infty)$ | **Score** IRFs | **Final rank** |
|---|---|---|---|---|---|---|---|---|---|
| $M_0$ | 0.06 | | ✓ | -0.54 | ✓ | | | 78/80 | $1^{st}$ |
| $M_1$ | 0.10 | | ✓ | -0.46 | ✓ | | | 75/80 | $2^{nd}$ |
| $M_5$ | 0.11 | | ✓ | -0.46 | ✓ | | | 69/80 | $3^{rd}$ |
| $M_4$ | 0.02 | | ✓ | -0.79 | | ✓ | | 79/80 | $4^{th}$ |
| $M_2$ | 0 | ✓ | | -1.63 | | | ✓ | 62/80 | $5^{th}$ |
| $M_3$ | 0 | ✓ | | -1.14 | | | ✓ | 60/80 | $6^{th}$ |

in bottom panel of table 1.8. This rank suggests that alternative methods of relaxing zero-restrictions improve the accuracy of the impact responses providing clearer explanations for the transmission of oil price shocks. Table 1.8 also shows that, under the same methodology, SVAR models with oil futures-spot spread provide higher score-rating than those including a proxy for global crude oil inventories.

In conclusion, we are able to provide a final rank in accordance with economic plausible estimates of oil supply and oil demand elasticities. On a practical level, implausible values for the price supply elasticities are specific to SVAR recursive models. According to table 1.3, a plausible range of price demand elasticity in the short and long run might be $(0; 0.6)$ and $[0.6; 1)$, respectively. In contrast, the last interval of table 1.9 is $[1; \infty)$ but it implies very implausible elastic oil demand curve.

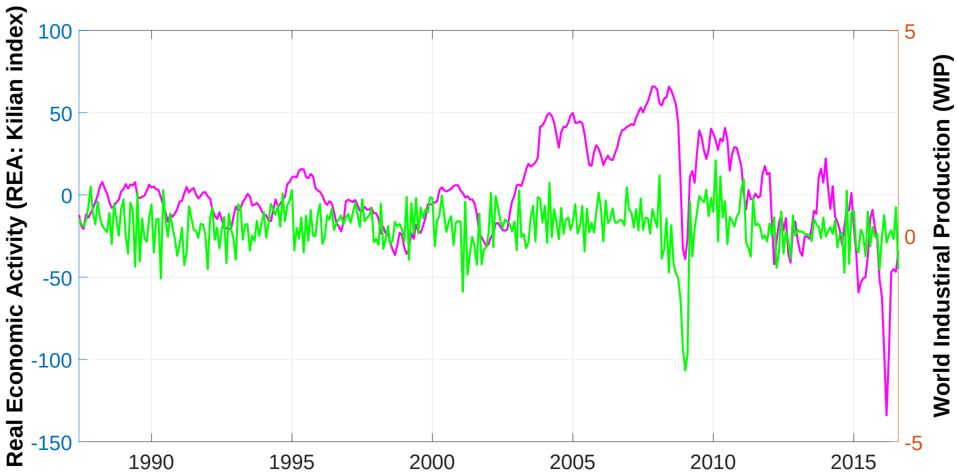
As reported in table 1.9, the short-run price demand elasticity implied by the benchmark model $M_0$ and the non-recursive models $M_1$ and $M_5$ are in the first range. As regards, $M_4$, its estimate of elasticity of oil demand is within the second interval. Finally, both $M_2$ and $M_3$ imply unrealistic estimates of their oil demand elasticities. Once we have classified all models according to their oil demand and oil supply elasticity estimates, the final rank can be obtained by sorting each model from the highest to the lowest score.

## 1.7 Robustness checks

The first robustness check relies on the work of Baumeister and Hamilton (2017), who uses the world industrial production index [36] as a proxy for global real output. As a second robustness check, we use the Brent spot price as a proxy for the global price of crude oil.

Figure 1.9 depicts two alternative proxies for the worldwide economic activity.

Figure 1.9: Global real economic activity measures




*Note:* Pink and green lines denote the real economic activity indicator (REA: Kilian's index) and the world industrial production (WIP) index, respectively. Since 2006, the WIP have included additional data for the non-OECD countries like, China, India, Brazil, Russia, South Africa and Indonesia.

The first indicator is the real economic activity index derived from the cost of international shipping. The second is the industrial production for OECD and non-OECD countries. Recently, the Kilian's index have exhibited some erratic behaviour that is hard to square with smooth fluctuations in the global business cycle. For example, the drop in the real economic activity index in the beginning of 2016. This decline is qualitatively similar to that reported

[36] An updated version of the WIP has been proposed by Baumeister and Hamilton (2017) and it can be downloaded from the following link: `https://sites.google.com/site/cjsbaumeister/research`

during the financial crisis. The main potential factors that might explain the increased in volatility in the aftermath of the financial crisis might be related to (1) the dependence on the cost of bunker fuel and hence on the price of oil, (2) the ship-building and scrapping cycle and (3) the increase in exposure of idiosyncratic shocks.

As regards the first point, in section 1.6.2 we have shown that the posterior distribution for $b_{rea,p}$ of the non-recursive model $M_4$ fails to take into account a direct feedback from price of oil to real economic activity index. This is not surprising since this indicator has been recently derived from the Baltic Dry Index (BDI). The latter is by definition independent from the fuel cost.

On the other hand, the feedback from price of oil to $rea$ might occur indirectly through the effects of aggregate demand shocks. In order to investigate the indirect feedback we should know the fuel cost share in the bulk dry cargo shipping. Fuel cost share represent private information which are difficult to retrieve.[37]

The second point refers to the role played by the ship-building and scrapping cycle. This is explained by the fact that, high shipping rates provide incentives for ship-building causing the size of fleet to rise and the volume of shipping rates to decline. However, it does not represent an attractive and solid explanation confirmed by the fact that increases in the amount of cargo vessels take years and the excess capacity can be absorbed through a substitution effect. The latter implies that less efficient bulk dry cargo vessels are scrapped in favour of new fleet.

[37] Kilian and Zhou (2017) discuss the case of a specific container carrier for which the impact of bunker fuel on the cost of dry bulk shipping was 25%, during the period 2014-2015. The authors state that, assuming a perfect pass-through, a 50% increase in the price oil crude oil would cause a 12.5% increase in the cost of shipping. However, this example might be not representative for the global cost of dry bulk shipping, since it involves only one shipping company. Therefore, the accuracy of the percentages of bunker fuel on the cost of dry bulk shipping requires further investigation.

Moreover, the qualitative analysis proposed by Kilian and Zhou (2017) shows that fluctuations in the Kilian's index during 2010-2016 was mainly driven by the demand side of the shipping market given the fact that the supply of bulk dry carries did not reflect significantly changes.

One last factor undermining the accuracy of $rea$ is its exposure to idiosyncratic shocks. In response to this issue, Kilian and Zhou (2017) shows that almost 60% of the decline in the real economic activity index occurred in early 2016 was explained by a global economic slowdown and the remaining fraction was related to idiosyncratic shocks in the market for iron ore.

The Kilian's index is not the only variable of economic activity for modelling the transmission of oil price shocks.

There are alternative measures for this purpose such as proxies for global real GDP, global industrial production, global steel production and commodity price index derived from a factor analysis. On a practical level, not all of these indicators are suitable for modelling the global price of crude oil.

For example, the "Quarterly World real GDP can" be considered a good proxy for global real output. However, this indicator has two drawbacks. First, it is available in quarterly frequency. Second, it does not reflect a stable relationship between changes in the real GDP and in the real commodity prices. This is also true for the most recent proxy for world real GDP expressed in monthly frequency.

A proxy for global real economic activity based on the aggregation of crude steel production has been proposed by Ravazzolo and Vespignani (2017). The authors exploit the role of steel as relevant input for many industries including constructions, transportation and manufacturing. The index offers several advantages very close to the Kilian's index. For example, it represents a global measure, it does not require a purchasing power parity weight across countries and it is a leading indicator with respect to real output.

On the other hand, this indicator presents two shortcomings. First, it is sensitive to any change in the number of steel-producing countries. Second, it might be over exposed to idiosyncratic supply shocks.

Analogous to the Kilian's index, idiosyncratic supply shocks can undermine the accuracy of the macroeconomic indicator. For this reason, researchers derive economic indicators by applying a factor analysis to a wide range of monthly commodity prices. This method allows to average out the idiosyncratic effects for each commodity by exploiting the cross-sectional dimension of the data. However, the most relevant drawback of such approach consists of the selection of the types of commodity prices to include in the factor analysis.

In principle, one should choose a basket of commodity prices by minimizing potential idiosyncratic shocks transmission from vertical integrated markets, as discussed in Alquist and Coibion (2014). The feasibility of this criterion remains an open question.

In the first robustness check we use the growth-rate of industrial production index as a proxy for global real output. This variable has two relevant shortcomings. First, it includes data for six non-OECD emerging economies (China, India, Brazil, Russia, South Africa and Indonesia) only prior to 2006, excluding the period in which China played a crucial role in driving the commodity prices. Second, depending on the transformations applied to the index, it might provide different paths. Specifically, log-linearly and detrended industrial production variable provides larger global economic slowdown than itself expressed in growth rate.

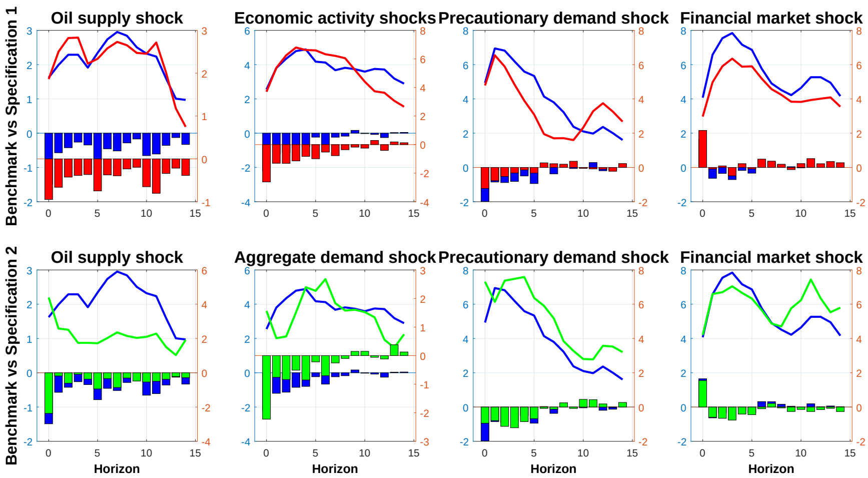
In this section we check whether the empirical results provided by model 1.1 are robust to changes in the variables of global business cycle and real price of crude oil. Therefore we estimate two alternative configurations of the benchmark SVAR model. The first specification includes the same variables except for the real economic activity index proposed by Kilian (2009). Thus, the Kilian's index is replaced with an updated measure of world industrial production as a proxy for global economic activity. As regards the second specification, the RACi is the only variable replaced with Brent spot price of oil.

In section 1.5 we have shown that, unexpected increases in the real price of oil driven by negative oil supply shocks and positive shocks to aggregate and precautionary demand for crude oil are associated with a drop in the oil futures-spot spread, on impact. On the other hand, positive financial market shocks cause an instantaneous increase in both the real price of oil and the oil futures-spot spread.

Figure 1.10 plots the price and spread responses to one-standard deviation structural shocks, for robustness checks. Three basic features emerge.

First, all impact responses are grounded on the economic theory. Second, the

Figure 1.10: Structural impulse responses for robustness check




*Note:* Red and green solid lines denote the RACi and Brent oil spot prices response estimates implied by specifications 1 and 2, respectively. Blue line refers to the RACi response based on the benchmark model. Analogous explanation is for the impulse responses of oil futures-spot spread, which are represented by bar charts.

row upper-panel of figure 1.10 shows that, in the benchmark model, a positive economic activity shock causes a smaller but much more persistent increase in the price of oil than specification 1.

As opposed, the rise in the price of crude triggered by a positive financial market shock is smaller in specification 1 than the benchmark model. The latter provides a peak price response after 4 months.

Notice that, the effects of an oil supply disruption and a positive precautionary demand shock on the global price of crude oil are similar in both models. Moreover, the impulse response of the oil-futures spot spread to each structural shock remains robust to changes in the economic activity measures.

Overall, the results obtained from the first specification exhibit striking qualitative similarities with the responses of oil price and the oil futures-spot spread implied by the benchmark model.

Finally, row bottom-panel of figure 1.10 suggests that the type of global price of crude oil matters for drawing conclusions in modelling oil price shocks.

If Brent prices were interpreted as international price of oil then the implied impulse response functions would not be as clear as in the case of US cost of imported crude oil (RACi).

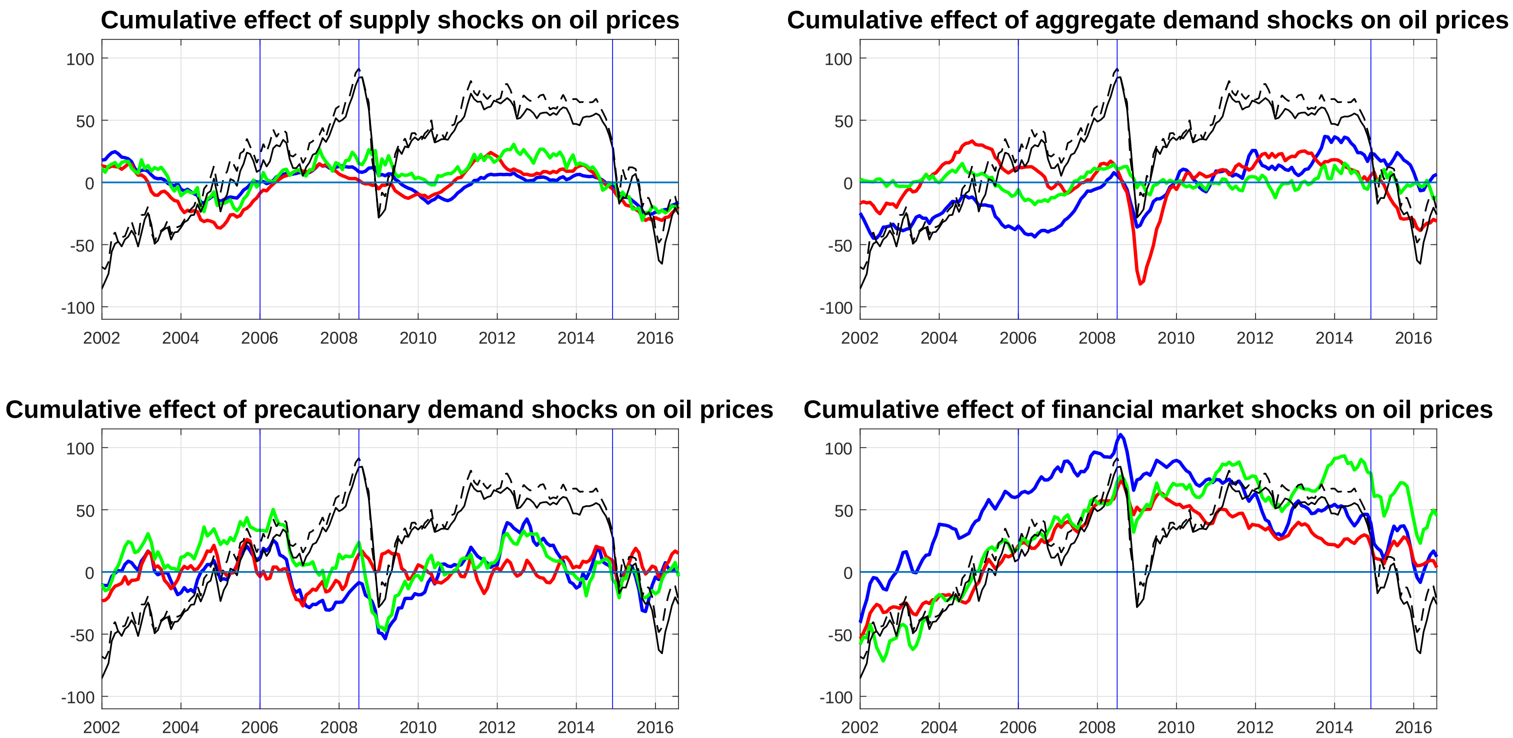
The response of Brent spot price to an oil supply disruption exhibits a fast decline in the first three months. A similar picture emerges in case of positive aggregate demand shocks.

These results suggest that the shape of the impulse response of Brent and RACi to oil supply shocks and aggregate demand shocks are different. In contrast, the path of price responses of RACi and Brent to precautionary demand and financial market shocks are qualitatively identical.

Despite a widespread beliefs that Brent price represents the international benchmark [38] of the spot price of oil, the empirical evidence shown in fig-

[38] Oil experts, Central Banks, and media consider Brent spot price as a reliable proxy for the global price of oil. The main reason is that it represents a reference price for North-west

Figure 1.11: Historical decompositions based on the SVAR model




*Note:* Black solid and dashed lines denote the RACi and the Brent spot oil prices, respectively. Solid blue line denotes the cumulative effect of each shock on the real price of crude oil implied by the benchmark model, as discussed in section 1.4. Red and green solid lines denote the historical decomposition of the real price of oil implied by specification 1 and 2, respectively. The reference period is 2002:1-2016:7 and vertical lines indicate the exogenous events in the global market for crude oil: financialization of commodity markets and great surge of oil price from 2003 until mid 2008 and the 2014-2015 slump.

ure 1.10 does not find sufficient support of it. In conclusion, we believe that the RACi is likely to be a better proxy for the price of crude oil in the global markets.

Figure 1.11 allows us to assess the quantitative importance of the structural shocks at each point in time, under robustness checks.

The effects of supply and precautionary demand shocks on oil prices (blue vs green lines) are very similar.

The impacts of aggregate demand shocks on RACi might be larger than Brent, during 2006-2008. Finally, the effects of financial market shocks on oil prices is not unique. In particular, 1.11 depicts higher price level for Brent and lower price level for RACi between 2008 and mid 2014.

It is not surprising to find out that the impact of aggregate demand shocks are different depending on the proxy (blue vs red lines) for global economic activity is applied to the analysis.

During the world financial crisis the aggregate demand shock played a crucial role in explaining the collapse of oil prices. The estimated historical decomposition associated with specification 1 (red line) shows that the slump in the real price of oil is primarily driven by a slowdown of the global economy.

Between 2006 and mid 2008, the effects of aggregate demand shocks measured by the Kilian's index plays a more relevant role in explaining the surge of the price of oil rather than its decline occurred beyond June 2008.

Finally, the recent global economic slowdown is associated with a decline in the real price of oil. The magnitude of this drop depends on the variables used to measure the global business cycle. As a result, the debate on which type of proxy for global real output should be included in VAR modelling is still an open question.

Europe, all West African, Mediterranean and recently for some South-east Asia crude oil.

In this respect, it is better to separate the contribution of aggregate demand shocks derived from the commodity price indices (i.e. the Kilian's index) to the real output measures (i.e. industrial production) because their economic meaning might be similar but not identical.

We believe that commodity price indices are linked to cost of production while real output measures are associated with the values of production. Therefore, it is not surprising to find out that the effects of aggregate demand shocks on the global price of crude oil are different in timing and magnitude depending on the types of proxy for global real economic activity.

## 1.8 Conclusions

There are two main important features in modelling the global price of crude oil. First, the selection of a proper set of endogenous variables. Second, the choice of the identification scheme that is applied to identify the structural shocks.

To our knowledge, we propose a model that differs for both aspects from those specifications proposed in the previous literature.

Most studies show SVAR models that include a physical proxy for crude oil inventories to describe the forward-looking behaviours of the oil traders.

In this analysis instead, we replace a physical proxy for global oil stocks with a financial measure of forward-looking expectations: the oil futures-spot spread. The latter is considered a proxy for the convenience yield but expressed with an opposite sign.

We show that the main benefits of using the oil futures-spot spread is to establish a direct link between physical and financial markets within the context of SVAR model. This allows to derive the real time market value of crude oil inventories held anywhere on Earth.

The other relevant contribution of this model consists of the economic interpretation of the residual structural shock. This can be viewed as an additional source of explanation which is able to capture the effects of oil price speculation and other forms of financial incentives that are implemented to keep crude oil off the physical market, causing the real price of oil to rise. We also show that the oil price speculation that are identified by oil market VAR models a' la Kilian and Murphy are conceptually different from the financial market shock discussed in this analysis. While both shocks are designed to capture an instantaneous increase in the amount of oil stocks for future consumption, the main difference stemming from the value of holding oil inventories. In the first case, the inventories' build-up is explained by an increase in the demand for storage. This causes an instantaneous reduction in the oil futures-spot spread which is mainly driven by a rise in the convenience yield. In the second case, the accumulation of crude oil inventories causes an increase in the oil futures-spot spread which is mainly explained by a decline of the convenience yield. We find evidence that financial market shocks have played an important role in explaining the rises in the price of oil during the period 2003-2008.

Finally this work provides an investigation of different types of oil market VAR models. The comparison based on the assessment of the impact responses for models with the same identification strategy offers evidence that the specification including oil futures-spot spread are better rated than those containing the proxy for global crude oil inventories. This suggests that the oil futures-spot spread represents a proper measure to capture the forward-looking expectations of oil traders.

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# Appendix Chapter 1

## 1.9 Identification strategy

Consider the generic representation of the reduced-form VAR model, with $n$ endogenous variables and $p$ lags:

$$y_t = \Theta_1 y_{t-1} + \Theta_2 y_{t-2} + \cdots + \Theta_p y_{t-p} + u_t \qquad t = 1, 2, \ldots, T \tag{1.7}$$

where $y_t$ is a $n \times 1$ vector of endogenous variables, $\Theta_1, \Theta_2, \ldots, \Theta_p$ are $p$ matrices of dimension $n \times n$ and $u_t$ is a vector of non-autocorrelated reduced-form innovations following a multivariate normal distribution $u_t \sim \mathcal{N}(0, \Sigma_u)$.
$\Sigma_u$ is a $n \times n$ symmetric positive definite matrix in which the error terms of individual equations can be simultaneously correlated. Since the reduced-form innovations display contemporaneous correlation it is difficult to provide an economic interpretation of the impulse responses function of the elements of the vector $u_t$.
On the other hand, $v_t$ denotes a $n \times 1$ vector of mutually uncorrelated structural errors term with the following variance covariance structure: $E_t(v_t v_t') = \Sigma_v$, where $\Sigma_v$ is normalized such that $\Sigma_v = I_n$. Notice that, $I_n$ represents an identity matrix of order $n$. The fact that, $\Sigma_v$ is a diagonal matrix implies that the

structural shocks can be economically interpreted in terms of shifts in demand and supply.

The structural disturbances can be obtained as follow: $u_t = \tilde{B}v_t$, where $\tilde{B}$ is a $n \times n$ matrix, such that $\tilde{B} \equiv B_0^{-1}$. In other words, $\tilde{B}$ coincides with the impact multiplier matrix and it captures the contemporaneous relations among the endogenous variables of the VAR model.

For the construction of the impulse responses function we need to identify the elements of the impact multiplier matrix $\tilde{B}$ by exploiting the algorithm discussed in Rubio-Ramirez et al. (2010). This is based on a set of sign restrictions that are directly imposed on the impulse response functions. The latter are constructed from consistent estimates of the reduced-form slope parameters. Therefore the set of impact multiplier matrix can be defined as the product between $B$ and any orthogonal square matrix $D$.

The matrix $B$ is lower triangular (with all zeros above the main diagonal) such that $BB' = \Sigma_u$. In other words, $B$ represents the factorization of $\Sigma_u$, such that $B = P\Lambda^{0.5}$, where $\Lambda$ is a $n \times n$ diagonal matrix in which the elements $\lambda_i$'s are the eigenvalues of $\Sigma_u$ and the columns of the matrix $P$ are the corresponding eigenvectors. Thus, the variance covariance matrix of the reduced-form VAR innovation can be also expressed as $\Sigma_u = P\Lambda P'$.

The $n \times n$ matrix $D$ is also referred to as the rotation matrix and is such that $D'D = DD' = I_n$, where $I_n$ is an identity matrix of order $n$. The algorithm proposed by Rubio-Ramirez et al. (2010) consists of two stages and it can be implemented as follow.

The first step is based on the construction of the $QR$ decomposition of a $n \times n$ matrix $X$ such that $X = QR$ where $Q$ is an orthogonal matrix and $R$ is upper triangular matrix with the elements on the main diagonal normalized to be positive. This step must be done in a repeated sampling by drawing the matrix $X$ from a independent standard normal distribution.

The second step defines $D = X'$ and it involves the construction of the set of admissible impulse responses function by using the following orthogonalization $\tilde{B} = BD$. If all the impulse response estimates satisfy the sign restrictions we retain $\tilde{B}$, otherwise we discard it and we go back to the first stage.

These two steps are computationally intensive because they are iterated 5 million of times. The estimation of the uncertainty is conducted under Bayesian method specifying Gaussian-inverse Wishart prior distribution for the reduced form parameters and a Haar distribution for the rotation matrix $X$. Thus, the credible set of the impulse responses function is constructed by applying the algorithm proposed by Rubio-Ramirez et al. (2010) to each draw of the posterior distribution for the parameters of the reduced-form VAR model.

The second identification strategy refers to the algorithm proposed by Baumeister and Hamilton (2015). This approach rather than impose directly sign restrictions on the impulse response function it consists of a specification of set of priors and an analysis of their implication in terms of likely impact structural shocks. The implementation of the estimation algorithm is based on three main steps.

First stage consists of a specification of informative prior beliefs, represented in form of density functions about the matrix $B_0$, the vector collecting the structural disturbances $v_t$ and the matrix $B_j$, for $j = 1, \cdots, 12$.

Prior for the elements of the contemporaneous structural matrix that are not known with certainty are collected in a vector ($\alpha$). Thus, let $p(B_0)$ be the joint prior distribution which is made by the product of *Student t* distributions of the elements collected in $\alpha$. Then, we need to specify priors for the inverse diagonal elements of the variance-covariance matrix of the structural errors $D$ conditional on $B_0$. The priors for $d_{ii}^{-1}$ (which denotes the element in row and column $i$ of matrix $D$) conditional on $B_0$ is given by a $\Gamma(\kappa_i, \tau_i)$ distribution, as follow:

$$p(D|B_0) = \prod_{i=1}^{n} p(d_{ii}|B_0) \tag{1.8}$$

where $\kappa_i/\tau_i$ and $\kappa_i/\tau_i^2$ represent the first and second moments of $d_{ii}^{-1}$, respectively. Notice that, the parameter $\tau_i$ depends on $B_0$ whereas $k_i$ does not.

Following Baumeister and Hamilton (2015) we calibrate the diagonal elements of $D$ from the residuals obtained by running OLS regressions from the univariate autoregressive models of order 12. Moreover, we set the prior mean for $d_{ii}^{-1}$ equals to the reciprocal of the diagonal element of a matrix $B_0 S B_0'$, where $S$ represents the sample variance covariance matrix of the univariate autoregressive models performed for each time-series.

We postulate $\tilde{b}_i$ is a row vector of random structural coefficients following a conditional normal multivariate distribution, $\tilde{b}_i|B_0, D \sim \mathcal{N}(m_i,\, d_{ii}M_i)$ where $m_i$ can be interpreted as the best guess about $\tilde{b}_i$ before seeing the data and $M_i$ represents the level of uncertainty about the standard Minnesota prior.

We follow the approach proposed by Doan et al. (1984) in which the behaviour for a generic time-series can be represented by a random walk process with $m_i = 0$ and great confidence to expect that coefficients related to higher lags are zero. [39]

In the end, the joint probability distribution of the prior information about the plausible values of the parameters is defined as:

$$p(B_0, D, B_j) = p(B_0)p(D|B_0)p(B_j|B_0, D) \qquad \text{for } j = 1, 2, ..., 24 \tag{1.9}$$

[39] Following Baumeister and Hamilton (2017) we need to set three different values for the hyper-parameters of the random walk prior for the lagged coefficients. Thus, we set the parameter controlling the overall tightness of the prior to 0.5. We set the parameter that governs how quickly the prior for lagged coefficients tightness to zero as lag increase to 1. Finally, we put prior on the parameter governing the tightness of the prior for the constant term to 100. The latter is used to make the prior on the constant term irrelevant.

In the second step, the Baumeister and Hamilton (2015)'s algorithm searches for a vector of values $\hat{\alpha}$ that solves numerically a maximization problem of the target function $q(\alpha)$. Thus, the vector $\hat{\alpha}$ provides a reasonable guess for the posterior mean of $\alpha$ while the matrix of second derivatives of $q(\alpha)$ with respect to $\alpha = \hat{\alpha}$ exploits information about the shape of the posterior distribution of $\alpha$.

In other words, the second stage sets the initial values for the elements of $B_0$ in order to inform the random-walk Metropolis Hasting algorithm, that is performed in the third step.

The last stage is designed to construct the joint posterior distribution of the parameters, that is $p(B_0, D, B|Y_T)$, where $Y_T$ represents the sample-data. According to Baumeister and Hamilton (2015) we proceed as follow.

First, we use the Metropolis Hasting algorithm to generate draws from the posterior distribution of the contemporaneous structural matrix, that is $p(B_0|Y_T)$. The iteration starts setting $\alpha^1 = \hat{\alpha}$ and for a generic step $l + 1$ we generate a candidate $\tilde{\alpha}^{(l+1)}$ as a sum of $\alpha^l$ and the product between three components: (1) a vector of independent standard *student t* variables with 2 degrees of freedom, (2) a scalar tuning parameter for 30% acceptance ratio and (3) the Cholesky factorization of the matrix capturing the curvature of the posterior distribution of the vector of unknowns parameters $B_0$.

Then, we compare the value of the target function evaluated in $\tilde{\alpha}^{(l+1)}$ and $\alpha^{(l)}$, respectively. If $q(\tilde{\alpha}^{(l+1)}) < q(\alpha^{(l)})$, we set $\alpha^{(l+1)} = \alpha^{(l)}$ with probability $1 - exp[q(\tilde{\alpha}^{(l+1)} - q(\alpha^{(l+1)})]$; otherwise we set $\alpha^{(l+1)} = \tilde{\alpha}^{(l+1)}$. The value $l$ indicates the number of iterations with the first $D$ burn-in draws included. Thus, starting with $l = D + 1$, for each $\alpha^l$ we generate $\delta^l_{ii} \sim \Gamma(k^*_i, \tau^*_i(B_0(\alpha^l)))$ for $i = 1, 2, 3, 4$ and take $D^l$ to be diagonal matrix whose elements $d^l_{ii} = 1/\delta^l_{ii}$. Finally, from the posterior distribution of the variance covariance matrix of the structural error terms we can further generate $\tilde{b}_i^l \sim \mathcal{N}(m_i^*, d_{ii}^l M_i^*)$ for $i = 1, 2, 3, 4$, where $\tilde{b}_i^l$ is the row vector of lagged structural parameters referred to the $i$th variable.

In the end, the triple $\{B_0(\alpha^l), D^l, B^l\}_{l=D+1}^{D+N}$ represents a sample size $N$ of posterior distribution:

$$p(B_0, D, B|Y_T) = p(B_0|Y_T)p(D|B_0, Y_T)p(B|A, D, Y_T)) \tag{1.10}$$

with the first $D$ burn-in draws equals to 200.000 and $N = 200.000$.

## 1.10 A simplified theoretical model

In this section we provide a stylized version of the theoretical commodity storage model in the spirit of Eastham (1939).

Figures 1.12 and 1.15 show the main features of the spot and the storage markets for crude oil. In the spot market the inverse demand function for current consumption is denoted by $D^{Cons}$ and it is defined as $P = f(Q^C)$ where $Q^C$ denotes the amount of crude oil demanded for consumption and $P$ indicates the spot price of a barrel of crude oil in the current period. The global oil production is denoted by $S$.

In the market for storage, the total amount of oil stocks held around the countries is denoted by $N$. We postulate that the oil stocks supply curve is predetermined in the short period while the demand for storage, denoted by $\Psi^D(N)$, is a decreasing and convex function of the level of inventories. Thus the marginal price of storage (or marginal convenience yield) is denoted by $\psi$.

The equilibrium in the spot market implies that the total demand for crude oil ($D^{Total}$) equals the sum of the quantity supplied ($S$) and the oil stocks carried on from the previous period ($N_{t-1}$), that is: $Q^T = S + N_{t-1}$. Moreover, the total amount of crude oil demanded is also defined as the sum of the current oil stocks held by the market and that quantity used for consumption, that is: $Q^T = Q^C + N$.

This means that the horizontal difference between $D^{Total}$ and $D^{Cons}$ represents the quantity demanded for storage at a specific spot price $P$ in any given period.

Putting together the two definitions of total demand for crude oil we yield with the following expression: $S - Q^C = \Delta N$ where $\Delta N$ is defined as $\Delta N = N - N_{t-1}$ and it represents the current oil inventories flow value. In other words, the market clearing condition implies a relationship between the current spot price $P$ and the current change in inventories $\Delta N$.

Figure 1.13(a) describes the effect of a negative supply shock in the global market for crude oil. An oil supply disruption represents a shift to the left of the simultaneous oil supply curve from $S_0$ to $S_1$ along the total demand for crude oil. As a result the quantity of crude oil declines from $Q_0^T$ to $Q_1^T$ and the real price increases from $P_0$ to $P_1$.

In the storage market the oil inventories will be draw down in order to smooth consumption with the consequence of a gradual increase in the marginal convenience yield, limiting the rise of the spot price of oil and causing the oil futures-spot spread to decline. Finally the marginal cost of storage will decline because of the reduction in oil inventories.

When the effect of the oil supply disruption vanishes, the supply curve and the real price of oil will go back to the original level and the replenishment of oil inventories will be reflected by a decline in the convenience yield.

Figure 1.14(a) illustrates the effect of a positive aggregate demand shock on the spot price of crude oil. This shock causes a shift to the right of the contemporaneous oil demand curve mainly driven by the global business cycle. Thus, current consumption moves from $D_0^{Cons}$ to $D_1^{Cons}$ along the oil supply curve and the demand for crude oil increases from $D_0^{Total}$ to $D_1^{Total}$. In order to mitigate the adverse effect of the shock on the real price of crude oil, the level of inventories will decline from $N_0$ to $N_1$. Thus, the increase in the real price of oil is limited up to $P_1$ and it is instantaneously followed by a drop in the oil futures-spot spread.

Figure 1.16(a) represents the effect of a positive precautionary demand shock on the real price of oil in the spot market. This shock can be interpreted as an increase in the demand for crude oil that is mainly driven by an upward shift of the demand for oil stocks.

In the storage market, between $t-1$ and $t$, the benefit of holding an extra barrel of crude oil increases from $\psi_A$ to $\psi_B$ causing a drop in the oil futures-spot spread at time $t$.

In the spot market, the total demand for crude oil increases from $D_{0A}^{Total}$ to $D_{1B}^{Total}$ motivated by a build-up of crude oil inventories.

On impact, the real price of oil overshoots in response to a positive precautionary demand shock moving from $P_{A(t-1)}$ to $P_{B(t)}$.

Beyond the impact period in the storage market crude oil inventories will be accumulated at lower rate moving from point B to C.

Analogously in the physical market the spot price of crude oil will decline from $P_{B(t)}$ to $P_{C(T)}$ defining a new long-run equilibrium denoted by $E_C$.

Finally, figure 1.17(a) shows the effects of a positive financial market shock. It represents an accumulation of crude oil inventories for reasons not already captured by the previous three structural shocks.

This shock is triggered by higher prices of the oil futures contracts.

For example, an unexpected positive $FM$ shock might be explained by a speculative purchase of oil futures contracts, arbitrage mechanisms used to restore the equilibrium between financial and physical markets, an increase in the global strategic petroleum reserves and other type of incentive to keep oil off the spot markets.

Therefore we can consider two possible cases through which the structural shock in question affects the real price of oil.

First channel consists of an increase in the total demand for crude oil from $D_0^{Total}$ to $D_1^{Total}$ followed by a simultaneous increase in the spot price of oil from $P_0$ to $P_1$.

The inventory accumulation causes a decline in the marginal convenience yield, from $\psi_0$ to $\psi_1$ followed by an increase in the costs of storage. This causes an instantaneous rise in the oil futures-spot spread.

The second channel is given by a shift to the right of the total demand for crude oil followed by an instantaneous shift to the left of the oil supply curve, from $S_0$ to $S_1$. This shock drives up the spot price of oil from $P_0$ to $P_2$ and the oil futures-spot spread, on impact. The rise in the oil futures-spot spread reflects a decline in the marginal convenience yield $\psi_0$ to $\psi_2$.

Finally, a reduction of speculative purchases in the futures market cause a drop in the expected pay-off of holding inventories. This is followed by a massive sell-off of oil stocks causing the spot price of oil to decline and the marginal convenience yield to increase. The latter reflects a drop in the oil futures-spot spread.

Figure 1.12: A stylized version of the theoretical commodity model (Eastham (1939))

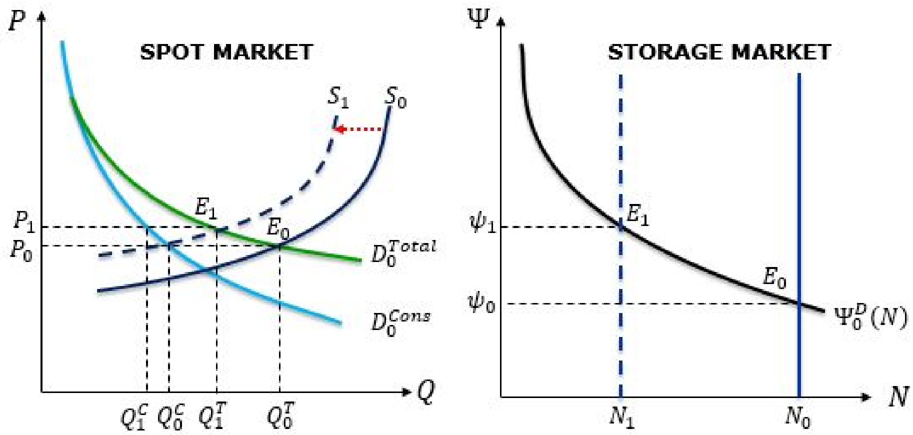


Figure 1.13: Negative oil supply shock

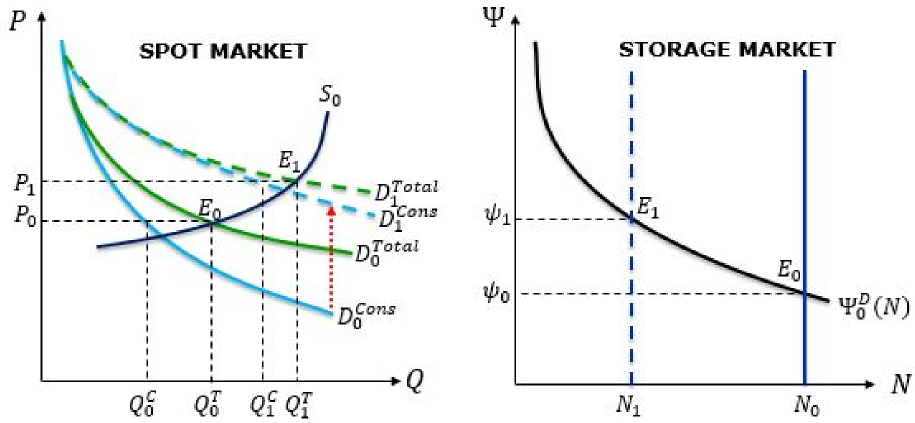


Figure 1.14: Positive aggregate demand shock

Figure 1.15: A stylized version of the theoretical commodity model (Eastham (1939))

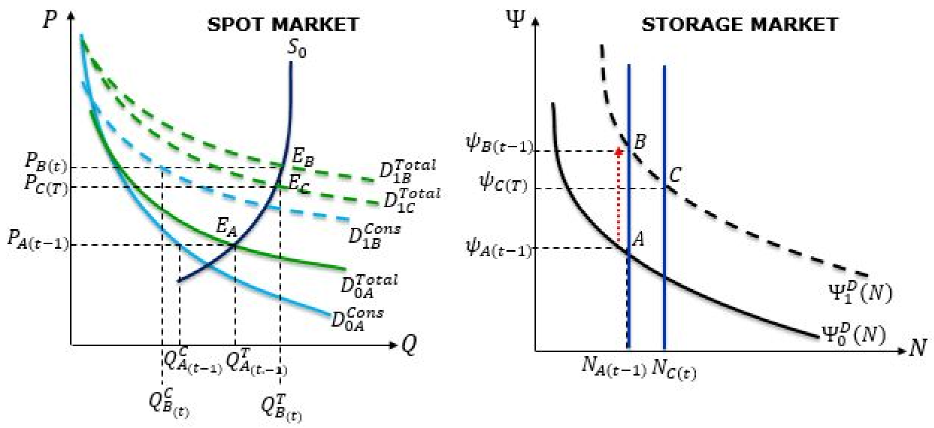


Figure 1.16: Positive precautionary demand shock

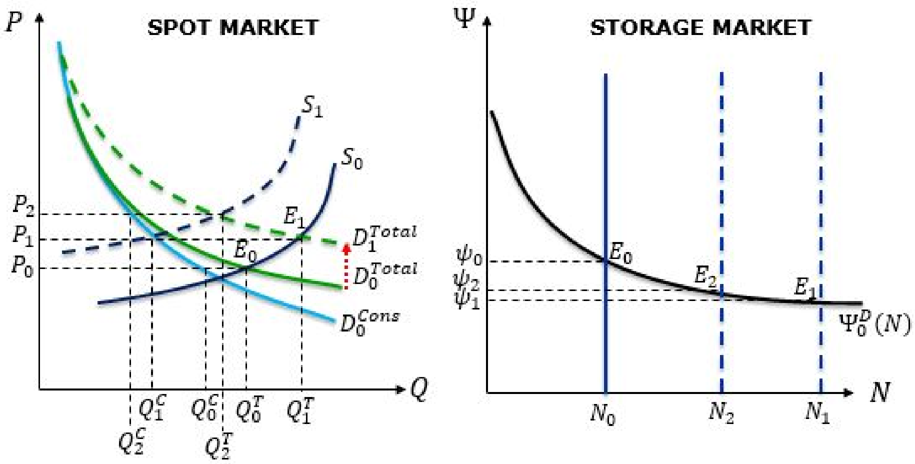


Figure 1.17: Positive financial market shock

Chapter 2

# Interpreting the oil risk premium: do oil price shocks matter?

# Interpreting the oil risk premium: do oil price shocks matter?

Daniele Valenti[a] Matteo Manera[b] Alessandro Sbuelz[c]

## Abstract

This paper provides an analysis of the link between the global market for crude oil and oil futures risk premium at the aggregate level. It offers empirical evidence on whether the compensation for risk required by the speculators depends on the type of the structural shock of interest. Understanding the response of the risk premium to unexpected changes in the price of oil can be useful to address some research questions, among which: what is the relationship between crude oil risk premium and unexpected rise in the price of oil? On average, what should speculators expect to receive as a compensation for the risk they are taking on? This work is based on a Structural Vector Autoregressive (SVAR) model of the crude oil market. Two main results emerge. First, the impulse response analysis provides evidence of a negative relationship between the risk premium and the changes in the price of oil triggered by shocks to economic fundamentals. Second, this analysis shows that the historical decline of the risk premium can be modelled as a part of endogenous effect of the oil market driven shocks.

**Keywords:** Crude oil risk premium, Bayesian SVAR model, Oil price speculation

**JEL Codes:** Q40 ,Q41, Q43, E32

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## 2.1 Introduction

The international market for crude oil is exposed to price risk. The latter can affect the economic performance of a large number of oil companies. Therefore commercial firms hedge against oil price volatility by taking part of the oil futures markets.

The risk premium arises because hedger offers to speculator (the counterparty side to the derivative contract) a monetary reward for non-diversifiable risk in the crude oil markets.

This paper emphasises the importance of the risk premium for two main reasons. First, it represents the opportunity cost that is accrued to commercial firms for hedging purposes. Second, it is an attractive investment return for oil speculators. This is motivated by the inflow of capital into crude oil futures markets from commodity index traders, also known as index funds. The latter are economic agents who wish to gain exposure to the oil futures price without holding the commodity in the physical market.

On a practical level institutional investors sell financial instruments in the over-the-counter (OTC) markets to commodity index traders. Therefore money managers who provide suitable instruments that replicate returns of commodity price indices hedge themselves by entering long in the oil futures markets. The following strategy can have impacts on the crude oil risk premium as discussed in Hamilton and Wu (2014). The authors show empirical evidence of a structural change in the average and the volatility of the risk premium in the crude oil futures contracts as a significant effect of the inflow of money from index traders.

In this paper we investigate the interaction between unexpected changes in the economic fundamentals of the global market for crude oil and oil risk premium at the aggregate level.

The methodology is based on a Bayesian structural vector autoregressive (BSVAR) model as discussed in Baumeister and Hamilton (2017). Relative to the existent literature on oil risk premium this work provides three main contributions. First, it offers an empirical evidence on whether compensation for risk required by oil speculators depends on the type of structural shock in question.
We document a negative relationship between the impact responses of the price of oil and the risk premium to shocks of the economic fundamentals in the global oil market.
This finding is consistent with theoretical framework based on the hedging pressure theory, the limits to the arbitrage theory and further considerations that will be presented and discussed in this analysis.
Moreover understanding the response of oil risk premium to unexpected changes in the price of oil is useful for some class of investors, such as speculators who usually take long positions in the oil futures markets.
Therefore this analysis addresses some research questions, among which: What is the relationship between crude oil risk premium and unexpected rise in the price of oil? On average, what should speculators expect to receive as a compensation for the risk they are taking on?
Second, this work provides a specific investigation for the risk premium in the crude oil market as opposed to most of the empirical analysis based on a "portfolio approach".
Understanding the economic factors driving the overall rate of return from a financial commodity portfolio (or index) can be misleading on several aspects. First of all, the commodity index cannot be a good proxy for the performance of a single asset class as referred to crude oil.
For example, the Standard and Poor's-Goldamn Sachs Commodity Index (SP-GSCI) represents the main benchmark for investment in the commodity mar-

kets but the share of crude oil futures contracts is only a fraction (about 40%) of its whole composition. For other indices like the Dow Jones-UBS Commodity Index (DJ-UBSCI) the total energy weight amounts to 30%. Moreover the weighting scheme of a commodity index might change over time.
Third, the choice of the econometric framework allows us to deal with reverse causality and consider the endogeneity of the crude oil risk premium with respect to macroeconomic and global oil market variables. This methodology is widely used in the empirical works for modelling the global price of crude oil, see Kilian (2009); Kilian and Murphy (2014); Kilian and Lee (2014).
The rest of the paper is set out as follows. Section 2.2 presents the literature review. Section 2.3 describes data and it offers stylised facts on the crude oil futures market. Section 2.4 discusses the methodology. Empirical results and some robustness checks are presented in section 2.5 and 2.6, respectively. Finally, sections 2.7 offers some conclusions.

## 2.2 Literature Review

According to the theory of normal backwardation proposed by Keynes (1930); Hicks (1939) and Kaldor (1939), on average the aggregate short hedging demand for futures outweighs the long hedging demand. As a result, to entice speculator to take a long side of the contract the crude oil futures price should be set below the expected future spot price.

For example the empirical analysis discussed in Bessembinder (1992); Bessembinder and Chan (1992) and De Roon and Veld (2000) find out that on average positive excess returns from holding futures contracts are correlated when hedgers are net short. Consistent with these findings Hong and Yogo (2012) show that the hedging pressure is an important determinant of crude oil risk premium.

In contrast, other studies such as Chang (1985) and Rouwenhorst and Tang (2012) do not provide robust results in linking the risk premium to position of speculators and hedgers. Gorton et al. (2013) and Alquist and Gervais (2013) highlight that changes in the net positions of oil traders do not predict oil prices movements. Conversely, the authors show that changes in oil prices help to predict changes in traders' positions on the oil futures market.

Recently, index speculators have been exposed to commodity indices within a context of a portfolio diversification as discussed in Cheng and Xiong (2014). Gorton and Rouwenhorst (2006) show that commodity futures returns derived from an equally-weighted index are low correlated with stocks and bonds but positively correlated with changes in inflation.

Hamilton and Wu (2014) propose a model describing the relationship between hedging demand from commercial producers, financial investors and the arbitrageurs. The equilibrium requires that the expected returns of futures prices depend on the arbitrageurs' net exposure to non-diversifiable risk in the crude oil market. The authors show that after 2005, the index-fund traders have considerably reduced the average level of the crude oil risk premium.

Studies by Irwin and Sanders (2012); Brunetti et al. (2013); Sanders and Irwin (2014); Brunetti and Reiffen (2014) investigate the role of speculation by exploiting the relationship between commodity index positions and the path of prices in energy futures markets.

In these works the authors conduct traditional time-series statistical test with mixed results to provide evidence of predictive link between commodity index investment and changes in energy futures prices. The empirical design behind this literature suffers from some limitations. First, these studies refer to a wide basket of commodities rather than the single market of crude oil. Second, these works treat position from the commodity index traders as exogenous to changes in futures prices leading to downward-biased estimates. Third, Granger-causality test says nothing about the causal relationship between futures prices and index speculators.

Another view consists of a link between the risk premium and the benefit derived of holding oil stocks. This economic view is typically based on the theory of storage.

As discussed in Gorton et al. (2013) and Erb and Campbell (2006) the convenience yield can be interpreted as a risk premium linked to the level of inventories which might be able to explain the term structure of the crude oil futures curve. As a result, higher levels of oil stocks might cause a reduction in the risk premium because the risk of stock-outs falls.

Alternative methodologies based on volatility models confirm that the rises in the crude oil risk premium are associated with higher price volatility in the underlying asset, see Moosa and Al-Loughani (1994) and Considine and Larson (2001).

Pindyck (2001) highlights that holding a commodity alone entails risk because the spot price of crude oil might covary positively with the global economy. Therefore the holders of a commodity will be rewarded for that risk in term of oil spot prices greater than relative current futures prices.

Finally, the crude oil futures risk premium might be also affected by macroeconomic factors. For example, Coimbra and Esteves (2004) find positive correlation between oil futures forecast errors and market expectation errors on economic activity at the world level. Pagano and Pisani (2009) highlight the importance of the US business-cycle indicators to provide precise estimates of oil futures prices adjusted for the risk premium. Analogously, Alquist et al. (2014) and Heath (2016) show that unspanned macroeconomic factors help to explain the behaviour of the crude oil risk premium.

## 2.3 Data and stylised facts on the crude oil futures market

The data we use in this work are monthly and cover the period 1983:4-2016:4. In this analysis two types of variables are employed: the global oil market variables and the oil risk premium predictors.
The former consists of a set of endogenous variables specific to the global market for crude oil. In this respect, we use the percentage changes in world crude oil production, the real economic activity (*rea*) index [1] proposed by Kilian (2009) and the real price of oil derived from te US refiners' imported acquisition cost of crude oil (RACi). Following Kilian and Murphy (2014), we use log-price in deviation from sample mean deflated by the US consumer price index. According to the current literature on interpreting the oil price shocks as terms of trade shocks, the RACi is likely to be a better proxy for the global price of crude oil. This postulates that, rises in the RACi triggered by exogenous events in oil markets cause a decline in the aggregate domestic income. Moreover, Valenti (2018) shows that the empirical results provided by RACi response estimates are qualitatively more precise than those derived from alternative measures of international oil prices, like the Brent spot price

[1] The real economic activity index *rea* is available from `http://www-personal.umich.edu/~lkilian/paperlinks.html`. This index requires raw data for individual dry bulk cargo freight rates. Following Kilian (2009), the construction of *rea* is based on three steps. First, one has to compute the period-to-period growth rates of each available series. Second, one has to compute the cumulative equal-weighted average of the growth rates, having normalized January of 1968 to unity. Third, the index has to be deflated by the US CPI index. Despite, our analysis starts in 1983 (because WTI oil spot prices are available from that period) we use the original version of the *rea* index. This approach does not undermine the accuracy of our empirical results. We point out that, in 1980, four series are involved for the construction of the index and they remain the same until 1983, the period in which we start our analysis. Therefore, there is not much difference from the cross average of the raw data for individual freight rates and their cumulative average growth rate if the index is constructed starting in 1960 or in 1983. The only difference is the change in the normalization applied to the starting value of the index but this does not compromise the economic meaning of the indicator for the future periods.

of oil.

The macroeconomic measure we use in this analysis is derived from the bulk dry cargo ocean shipping freight rates and it is a proxy for the volume of international shipping in the commodity markets.

The *rea* index offers some important advantages for the identification of oil price shocks since it represents a monthly, direct, and leading measure of global business cycle, as pointed out by Kilian and Zhou (2017).

A widely accepted issue of the *rea* index refers to its potential exposure to idiosyncratic shocks. The latter might undermine the accuracy of this indicator as a measure of global business cycle. Therefore in section 2.6 we highlight the main results by replacing the *rea* index with a global measure of real output, that is the monthly industrial production index as discussed in Baumeister and Hamilton (2017).[2]

Finally, this work focuses on the crude oil risk premium which represents the predictable pay-off of an oil futures contract held to maturity. As opposed to the previous variables crude oil risk premium is not observable and it must be estimated from the data.

Therefore to derive the monthly realized excess return we use three months futures contracts price as the end-of-month value and close daily spot price traded on WTI market. [3]

As regards the set of risk premium predictors we include both macroeconomic and financial data. Table 2.1 reports a summary of the explanatory variables used for the estimation of the risk premium.

We use changes of the US consumer price index to derive a monthly measure for

[2]The monthly industrial production index is available from `https://sites.google.com/site/cjsbaumeister/research` and it includes data for OECD and non-OECD countries. The latter refer to economies like China, India, Brazil, Russia, South-Africa and Indonesia.

[3]We select futures price from WTI market since it represents the simplest way to obtain the longest available series to compute realized log-returns of a crude oil futures investment.

annual inflation rate ($inf$). Some empirical studies find out that the expected ($ei$) and unexpected ($ui$) component of the inflation rate is positively correlated with prospective returns of a commodity futures investment. This is consistent with the view that investors use crude oil futures contracts to hedge against inflation risks.

Following Casassus and Collin Dufresne (2006) we consider a proxy for the

Table 2.1: **List of predictors for the estimation of the risk premium**

| Id | Predictors | Descriptions |
|---|---|---|
| 1 | $inf$ | Annual CPI inflation rate |
| 2 | $ei$ | Expected US inflation |
| 3 | $ui$ | Unexpected US inflation |
| 4 | $cts$ | Change in the term structure yield curve |
| 5 | $cdp$ | Change in the default premium |
| 6 | $jbp$ | Junk bond premium |
| 7 | $cli$ | Composite leading indicator |
| 8 | $cip$ | Annual changes of U.S industrial production index |

slope of the yield curve in order to capture the relationship between the US government bond and crude oil market. We refer to the change in the term structure yield curve ($cts$) which is defined as the difference between the 10-Year Treasury constant maturity rate and the Treasury Bill of maturity 3-months.

Variation in liquidity plays an important role in explaining the factor structure of the global business cycle and it can be correlated with the risk premium. Therefore the analysis takes into account other two indicators. The first is the change in default premium ($cdp$) defined as the difference between Moody's Baa corporate bond yield and 10-year treasury constant maturity rate. The second indicator is called junk bond spread ($jbs$) and is derived as differences between Baa and Aaa corporate bond yields rated by Moody.

Moreover empirical results by Pagano and Pisani (2009) suggest that the risk premium in the commodity markets can be strongly affected by fluctuations in the business cycle of the global economy. Therefore this analysis includes the composite leading indicator (*cli*) and the yearly changes in the US industrial production index (*cip*).

### 2.3.1 The estimation of the crude oil risk premium

The oil risk premium represents the average returns that long investors expect to receive as a reward for non-diversifiable risk in the crude oil futures market. The risk premium is not observable but it can be estimated from the data. In this analysis we follow two different methodologies.

The first approach relies on a multivariate linear regression model. The second method is based on a Gaussian affine term-structure model in which time-varying crude oil risk premium depends on three latent factors. The first two factors are identified as the level and the slope of the term structure futures curve while the last can be though as a proxy for measurement error.

Regarding the first methodology we define the log realized excess returns of a crude oil futures investment as $er_{t+3} = ln\left(\frac{S_{t+3}}{F_{t,3}}\right)$.

Specifically, $F_{t,3}$ denotes the price of futures contract at the end of the day of month $t$ (with maturity 3-months) and $S_{t+3}$ is the corresponding realized daily spot price at the next 3-months from period $t$.

In this analysis we provide four alternative measures of crude oil risk premium in order to assess the robustness of the empirical results. We estimate the first-three measures of risk premium as follow:

$$rp^{(1)}_{t+3} \equiv \hat{er}_{t+3} = \hat{\alpha} + \hat{\beta}_1 inf_t + \hat{\beta}_6 jbp_t + \hat{\beta}_7 cli_t \qquad \text{for } t = 1, 2, \ldots, T \tag{2.1}$$

$$rp^{(2)}_{t+3} \equiv \hat{er}_{t+3} = \hat{\alpha} + \hat{\beta}_3 ui_t + \hat{\beta}_4 cts_t + \hat{\beta}_7 cli_t \qquad \text{for } t = 1, 2, \ldots, T \tag{2.2}$$

$$rp_{t+3}^{(3)} \equiv \hat{er}_{t+3} = \hat{\alpha} + \hat{\beta}_2 ei_t + \hat{\beta}_5 cdp_t + \hat{\beta}_8 cip_t \qquad \text{for } t = 1, 2, \ldots, T \qquad (2.3)$$

where $T = 400$ , $\hat{\alpha}$ and $\hat{\beta}$ are consistently estimated by ordinary least squares (OLS), as pointed out by Baumeister and Kilian (2016). Although the risk premium regression analysis is widely accepted in the academic literature some concerns might arise about the selection criteria of the exogenous variables.

Therefore we provide an alternative estimate of risk premium based on oil futures prices, only. This approach stems from an affine factor structure model as developed by Hamilton and Wu (2014).

The authors propose a model of the time-varying risk premium that imposes an affine factor structure which is common for oil futures prices and the economic fundamentals of the global market for crude oil.

The risk premium is identified by the difference between the observed futures prices and the rational expectation of future spot price. The latter depends on the risk price parameter which is thought as an affine function of the latent variables.

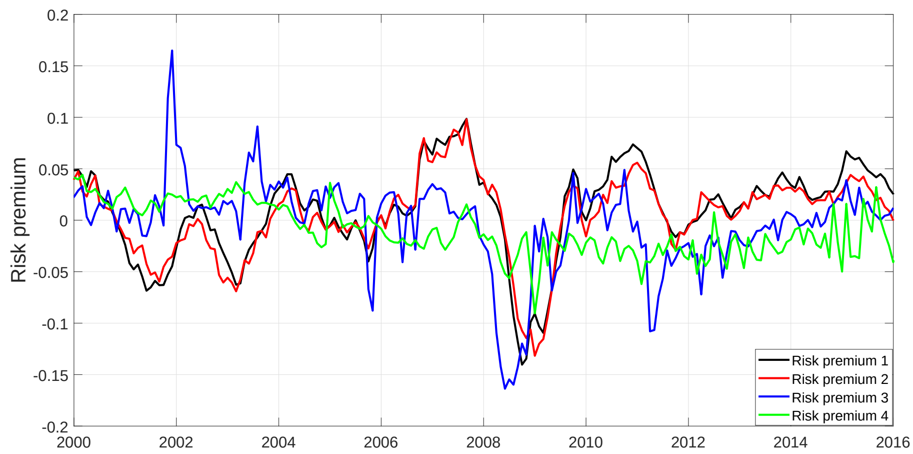
To estimate an affine term structure model we postulate the existence of three factors. The first-two factors represent level and slope of the nearest three futures contracts while the third factor is usually interpreted as measurement error.

Data are collected such that the maturity of futures contracts changes with each observation. Thus, implementation of the term structure model only requires oil futures prices collected in an unbalanced dataset in which the panel structure is given by different maturities and the monthly time-series dimension is made by the futures price on the last day of each week.

Following Hamilton and Wu (2012) the set of parameters included in the affine term structure model can be derived by applying the method of minimumchi-square estimation (MCSE) to the unrestricted reduced form estimates. In this way it is possible to infer the crude oil risk premium as difference between the oil futures price based on the structural parameters under risk-neutrality assumptions and the observed oil futures price that characterize the real world dynamic. [4]

Figure 2.1 plots four alternative estimates of the risk premium based on the

Figure 2.1: Risk premium regression estimates.




*Note:* Figure 2.1 plots the risk premium estimates across different specifications and methodologies over the period January 1990 - April 2016.

methodologies and the specifications that have been previously discussed. Two basic features emerge. First, significant similarities can be seen between the pairs of risk premium estimates. In particular, the first and the second measures of risk premium show highly positive correlation (0.93) over the entire sample. This becomes stronger (0.96) from January 2000 to April 2016. Moreover the risk premium estimate implied by the affine term structure model,

[4]Hamilton and Wu (2012) show that the MCSE minimizes a quadratic form in the difference between the reduced-form parameters implied by the structural model and the ols estimates derived from the reduced-form model. The quadratic form corresponds to the information matrix and the MCSE is asymptotically equivalent to full-information maximum likelihood estimator.

$rp_{t+3}^{(4)}$, is positively correlated with $rp_{t+3}^{(3)}$. In particular their correlation ranges from 0.32 (January 1984 - April 2016) to 0.46 (January 2000 - April 2016). Second, the last two measures of crude oil risk premium document a systematic downward shift of their average level.

Following Baumeister and Kilian (2016), we compute the mean squared prediction error (MSPE) ratio between the rational expectation of future spot price and the random-walk process in order to assess the accuracy of each risk premium estimate. Rational expectations of future spot price equals the futures prices adjusted for the crude oil risk premium. A case of MSPE ratio below one indicates an improvement in the accuracy of the random-walk process.

Table 2.2 reports the predictive accuracy of risk-adjusted futures price and the p-value associated with the MSPE reduction based on the test of Clark and West (2007).

Table 2.2: **Predictive accuracy of risk-adjusted futures price.**

| Risk premium | Mean squared prediction ratio | p-value |
|---|---|---|
| $rp_{t+3}^{1}$ | 0.92 | 0.03 |
| $rp_{t+3}^{2}$ | 0.95 | 0.03 |
| $rp_{t+3}^{3}$ | 0.88 | 0.05 |
| $rp_{t+3}^{4}$ | 0.82 | 0.02 |

### 2.3.2 Stylised facts on the crude oil futures market

Broadly speaking, participants in the oil futures market can be classified into three categories: hedgers, speculators and arbitrageurs.

The hedgers have economic interests in the physical market and they hedge against price risks by holding opposite positions in the spot and futures markets at the same time.

For example, an oil producer can lock in the price of crude oil production by selling a certain amount of futures contracts in anticipation of a later spot market sale. In contrast, an oil consumer can hedge against rising crude oil prices by buying a given number of futures contracts in anticipation of an actual physical market purchase. Although hedging activities represent the simplest way to manage price risks they could also affect the total revenues accruing to both consumers and producers.

The oil speculators are not interested in making (or taking) delivery of the commodity in the physical market but they buy (or sell) paper barrels to make profits as an opportunity for a capital gain in anticipation of price changes or as component of a diversified portfolio.

For example, the Commodity Pool Operators (CPO's) are investment vehicles that collect capital from a large number of investors, through a public or private offering, in order to facilitate investment opportunities in a portfolio of commodity futures.

The CPO's usually delegate the Commodity Trading Advisors (CTA's) who are professional money managers able to engage futures transactions in the derivative markets. Analogously the hedge funds invest on behalf of rich people in conjunction with other investment products like stocks, currencies and bonds.

As a result the participation of financial institutions such as banks, hedge, mutual and pension funds, money managers can add liquidity to crude oil futures market serving as a counterparty for the hedgers.

The arbitrageurs are the third class of actors who attempt to profit from any markets' price discrepancies.

All categories above mentioned are easier to separate in principle than in practice but their definitions reported in this analysis are consistent with those proposed by the Commodity Futures Trading Commission (CFTC).

The following regulatory agency breaks down the number of outstanding short and long futures contracts for crude oil on the basis of two macro categories: the "commercial" and "non-commercial" firms.

The former include physical participants such as producers, merchants, processors and end-users that have a direct interest in physical oil production, consumption and trade.

The latter are mainly made by financial participants like money managers and hedge funds that are interested in trading futures contracts for investment purposes.

In this context commercial firms are considered hedgers while non-commercial firms are treated as speculative traders.

At first sight it might be questionable to assume that commercial firms are only hedgers. For example a producer (or consumer) can hedge only a fraction of its physical underlying taking implicitly a speculative position, see Fattouh et al. (2013).

However, since in this analysis the risk premium is defined as a monetary reward accrued to speculators for their non-diversifiable risk in the commodity market, it is reasonable to refer to a non-commercial firm as a speculative trader.

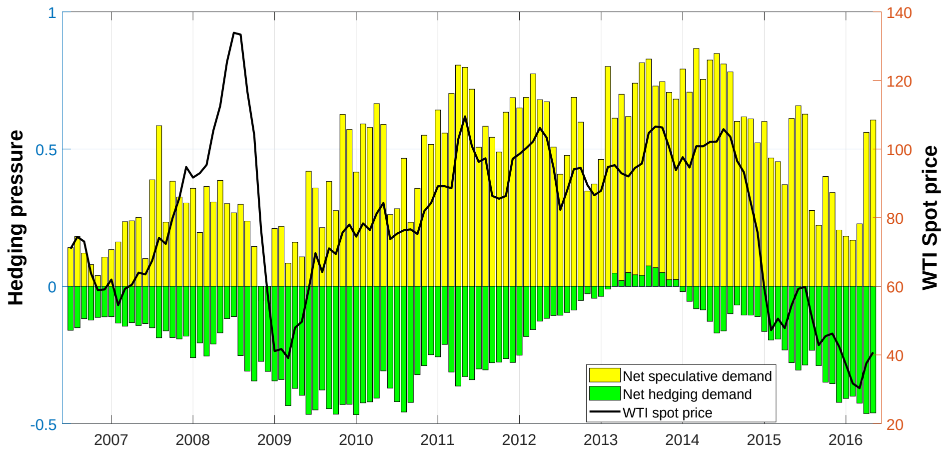
The hedging pressure theory states that the risk premium arises from the interaction between hedgers and speculators and it becomes higher (in absolute value) when the hedging demand increases.

The open interest represents the number of derivative contracts held by both commercial and non-commercial firms at the end of a trading day. This is a proxy for the flow of money injected into the futures market and it can be used to define an aggregate measure of hedging (or speculative) pressure.

Therefore we define the net-hedging demand as a ratio between the net and gross positions of the futures contracts referred to commercial firms. Analogously, the same logic applied to non-commercial firms yields to a measure of net-speculative demand. This last can be also interpreted as proxy for net-hedging supply.

Interestingly, the CFTC considers financial institutions called swap dealers

Figure 2.2: Hedging pressure indicators.




*Note:* Figure 2.2 plots the WTI spot prices combined with the hedging pressure indicators over the period January 2006 - April 2016. Green histograms refer to the net-hedging demand from commercial firms. Negative values indicate that hedgers are net-short. Green histograms refer to the net-speculative demand from money managers. Positive values indicate that speculators are net-long.

as commercial firms. Although these entities represent investment banks and commodity brokers/dealers, they act as intermediaries for producers and consumers suggesting that their positions on futures market should reflect hedging purposes. However, it may not always be obvious to understand whether swap dealers operate for commercial firms or not. For this reason we do not include the positions of swap dealers on the derivative market in the definition of hedging pressure measure.

Figure 2.2 plots the monthly WTI spot price combined with the net positions held by both the hedgers and the speculators.

It is important to note that an investor might hold both long and short positions in the futures market. In particular for every contract that one trader is long there is another trader who is short such that the outstanding value of long and short futures contract is exactly offsetting.

Figure 2.2 shows that on average the hedgers are net-short and speculators are net-long. Interestingly, hedgers seem to follow price trend: they increase their net-short positions when the spot price falls and move from short to long positions when spot price rises. On the other hand, speculators seem to change their positions in the futures market with the object to replicate the spot price of oil, providing market liquidity.

## 2.4 Econometric method

The methodology is based on a Bayesian structural vector autoregressive (BSVAR) model inspired by Baumeister and Hamilton (2017). In this section we provide an economic explanation for each of the structural equations and the corresponding informative prior distributions. Further details of the identification strategy and the Bayesian algorithm as proposed by Baumeister and Hamilton (2015) are reported in 2.8.

The SVAR model is the following:

$$Ay_t = c + \sum_{j=1}^{24} B_j y_{t-j} + v_t \tag{2.4}$$

where $A$ is the matrix of instantaneous structural parameters and $c$ is the vector of constant terms. The vector of endogenous variables is $y_t$ and it includes the percent change in global crude oil production ($q_t$), the global real economic activity ($rea_t$), the real price of crude oil ($p_t$) and the crude oil risk premium ($rp_t$). The structural representation considered in 2.4 is based on a system of four equations:

$$q_t = a_{q,p} p_t + \tilde{b}_1 x_{t-1} + v_{1t} \tag{2.5}$$

$$rea_t = a_{rea,q} q_t + a_{rea,p} p_t + \tilde{b}_2 x_{t-1} + v_{2t} \tag{2.6}$$

$$p_t = a_{p,q} q_t + a_{p,rea} rea_t + \tilde{b}_3 x_{t-1} + v_{3t} \tag{2.7}$$

$$rp_t = a_{rp,q} q_t + a_{rp,rea} rea_t + a_{rp,p} p_t + \tilde{b}_4 x_{t-1} + v_{4t} \tag{2.8}$$

where $\tilde{b}_1, \tilde{b}_2, \tilde{b}_3$ and $\tilde{b}_4$ are row vectors of structural lagged coefficients [5] related to the first-four equations and $x_{t-1}$ is a column vector including a constant

[5] The generic $\tilde{b}_i$ contains all structural lagged coefficients of the $i^{th}$ equation belongs to the first row of $B_j$, for $j = 1, \cdots, 24$. In other words, $\tilde{b}_i$ has a dimension $(n \times m + 1)$ where $n$ and $m$ are the numbers of endogenous variables and lags, respectively.

and the past variables.

The oil supply equation is given by 2.5. It is a function of only one contemporaneous structural parameter $a_{q,p}$ which represents the short-run price elasticity of oil supply.

The real economic activity modelled in equation 2.6 is instantaneously affected by the global oil production and the real price of crude oil due to $a_{rea,q}$ and $a_{rea,p}$, respectively.

The inverse demand function of the global market for crude oil is defined in equation 2.7. The structural coefficient $a_{p,q}$ is the reciprocal of short-run price elasticity of oil demand. The parameter $a_{p,rea}$ represents the effect of changes in the real economic activity index on the global price of crude oil.

The risk premium estimate modelled in equation 2.8 is contemporaneously affected by all endogenous variables that are considered in this analysis.

Finally $v_t = (v_{1t}, v_{2t}, v_{3t}, v_{4t})'$ denotes a vector of structural innovations with the following variance covariance structure: $E_t(v_t v_t') = D$ and $E_t(v_t v_s') = 0$ if $t \neq s$. The fact that $D$ is a diagonal matrix implies that the structural shocks can be economically interpreted in terms of shifts in demand and supply.

In particular, the first shock ($v_{1t}$), oil supply shock, is the unexpected changes in the global oil production. The second shock ($v_{2t}$), aggregate demand shock, reflects a rise in the demand for crude oil and other industrial commodities driven by fluctuations in the global business cycle. The third shock ($v_{3t}$), precautionary demand shock, is related to a unanticipated change in the demand for crude oil for future consumption.

Finally, the fourth shock ($v_{4t}$) is called risk premium shock and it is designed to capture unexpected changes in the risk premium which are not driven by the first-three structural shocks. For example, it might reflect an increase in the price of risk and/or capital constraints, difficulty to achieve a diversified investment portfolio, and the existence of profitable opportunities from other markets.

The matrix summarizing the simultaneous structural relations among the endogenous variables can be denoted as follow:

$$A = \begin{pmatrix} 1 & 0 & -a_{q,p} & 0 \\ -a_{rea,q} & 1 & -a_{rea,p} & 0 \\ -a_{p,q} & -a_{p,rea} & 1 & 0 \\ -a_{rp,q} & -a_{rp,rea} & -a_{rp,p} & 1 \end{pmatrix} \tag{2.9}$$

The first row of matrix $A$ characterizes the oil supply equation, as reported in 2.5. For the short-run price supply elasticity $a_{q,p}$, we assign *student* $t(c_{q,p}, \sigma_{q,p}, \nu_{q,p})$ positive truncated distribution, with mode at $c_{q,p} = 0.1$, scale parameter $\sigma_{q,p} = 0.2$ and degrees of freedom $\nu_{q,p} = 3$.

A small value of oil supply elasticity reflects the large costs of production for the oil industry, see for example Pindyck (1994, 2001). Moreover, our choice of prior mode for $a_{q,p}$ is consistent with the empirical studies of Baumeister and Hamilton (2017) and Caldara et al. (2017).

The second row of $A$ includes the structural parameters of the real economic activity equation. In this respect, we are confident to put a prior *student t* density function for $a_{rea,p}$ with mode at $c_{rea,q} = 0$, scale parameter $\sigma_{rea,q} = 0.1$ and $\nu_{rea,q} = 3$ degrees of freedom. Since the real economic activity index is derived from a bulk dry cargo ocean shipping fright rates, by construction, changes in amount crude oil production (liquid commodity) do not directly affect the proxy for global real economic activity.

As regards the effect of changes in the real price of crude on the real economic activity index ($a_{rea,p}$), we put a relative uninformative *student t* prior distribution, with at mode $c_{rea,p} = 0$, scale parameter $\sigma_{rea,p} = 0.5$ and $\nu_{rea,p} = 3$

degrees of freedom, negative truncated. A negative truncation density is consitent with the view that an increase in the real price of oil causes a reduction in the economic activity index, as pointed out by Kilian (2009); Kilian and Murphy (2014).

In matrix 2.9 the structural coefficient $a_{p,q}$ represents the reciprocal of short run price elasticity of oil demand. We put a *student* $t(c_{p,q}, \sigma_{p,q}, \nu_{p,q})$ prior distribution with mode at $c_{p,q} = -3$, scale parameter $\sigma_{31} = 0.1$ , $\nu_{31} = 3$ degrees of freedom and truncated to be negative. Our prior mode for $a_{p,q}$ implies a short-run price demand elasticity centred around -0.33. This last value is coherent with the empirical literature on estimating the price elasticity of crude oil demand in the short run, see for example West and Williams (2004, 2007) and Tiezzi and Verde (2014). The structural coefficient $a_{p,rea}$ represents the effect of changes in economic activity on the real price of crude oil. Despite the $rea$ is not a direct measure of real output we exploit some specific results provided by Kilian and Murphy (2012) and Valenti (2018). According to the first study, the effect of economic activity on the real price of crude oil from the impact multiplier matrix is positive and around 2. The second analysis finds that the posterior median for the structural coefficient $a_{p,rea}$ has mass of probability centred around 1.4, given a completely agnostic prior *student* $t$ density function. As a result, we assign *student* $t(c_{p,rea}, \sigma_{p,rea}, \nu_{p,rea})$ prior distribution with mode at $c_{p,rea} = 1.4$, scale parameter $\sigma_{p,rea} = 0.2$ , $\nu_{32} = 3$ degrees of freedom and truncated to be positive.

Finally for the parameters of the risk premium equation we assign completely uninformative prior $t$ *student* distributions, with location parameter $c_i = 0$, scale $\sigma_i = 100$ and degrees of freedom $\nu = 3$.

The structural matrix 2.9 involves four zero-restrictions hypothesis. Specifically, two exclusion restrictions on the elements of the global oil supply equation, that is $a_{q,rea} = a_{q,rp} = 0$. The latter are consistent with the assumption that global oil production does not respond to any change in the economic activity and crude oil risk premium, within the same period. This implies that, changes in the global crude oil production are only caused by changes in real price of oil. Finally, given the forward-looking nature of the risk premium we impose the remaining two exclusion restrictions on the structural parameters $a_{rea,rp}$ and $a_{p,rp}$.

The prior density of matrix $A$ is given by the product of all *student t* densities of each structural parameter subject to the sign restrictions previously discussed.

## 2.5 Empirical results

**Impulse response analysis.** In this section we proceed to the analysis of the dynamic responses of the endogenous variables to each structural shock. The shocks have been normalized such that they imply an increase in the real price of oil.

The empirical results reported in this section use the estimate of crude oil risk premium derived from the affine term structure model proposed by Hamilton and Wu (2014).

Figure 2.3 depicts the median impulse responses of oil production, real economic activity and price of oil to oil supply and oil demand shocks together with the corresponding pointwise 68% percentiles of the posterior distribution. The impulse response estimates imply that an unexpected oil supply disruption causes a contemporaneous drop in the global crude oil production. This shock is also associated with an increase in the price of oil and a decline in the real economic activity, on impact.

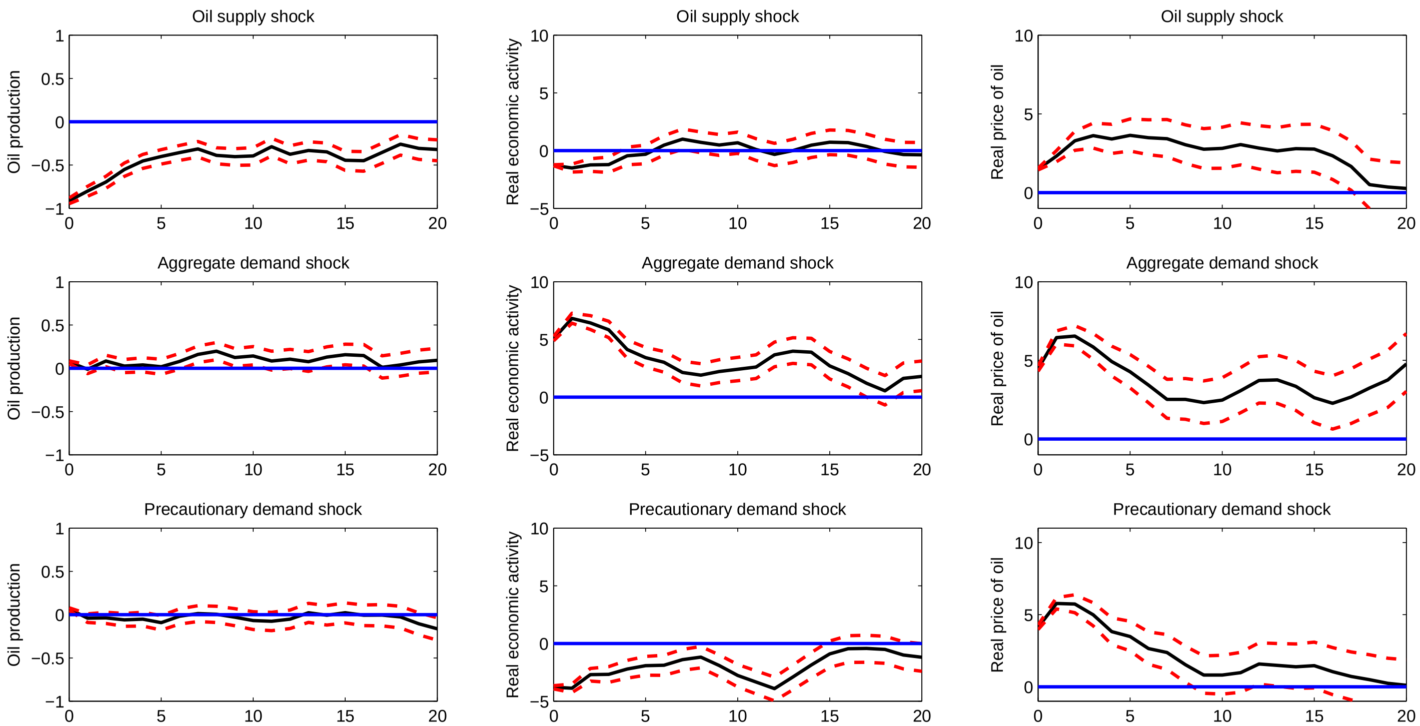
An unanticipated positive aggregate demand shock causes an instantaneous increase in the real economic activity, in the global oil production and in the real price of crude oil.

Finally a positive precautionary demand shock causes a contemporaneous increase in the global oil production accompanied by an hump-shaped response of the real price of oil. The impact response of the real economic activity to a positive precautionary demand shock is negative.

Figure 2.3 provides empirical evidence that the dynamic responses of global oil market variables to each structural shock are consistent with the empirical results of Kilian (2009); Kilian and Murphy (2014); Kilian and Lee (2014) and Baumeister and Hamilton (2017).

Figure 2.4 plots the median impulse response function of the oil futures risk

Figure 2.3: Median impulse responses of global oil production, real economic activity and price of oil to oil market shocks




*Note:* Figure 2.3 plots the Bayesian posterior median responses to one-standard deviation structural shocks. Black lines indicate the impulse response estimates based on structural models satisfying the identification structure. Dashed lines indicate the 68% credible region.

premium to each structural shock. There is empirical evidence that the crude oil risk premium responds to oil price shocks differently, depending on the cause behind the shock. Specifically, a positive risk premium shock causes an immediate jump in the oil futures risk premium, but only temporarily. In contrast, an oil supply disruption and a positive aggregate demand shock causes a negligible instantaneous decline in the crude oil risk premium. Notice that, beyond the impact period, the economic activity shock causes a more persistent reduction in the risk premium than a negative supply shock.

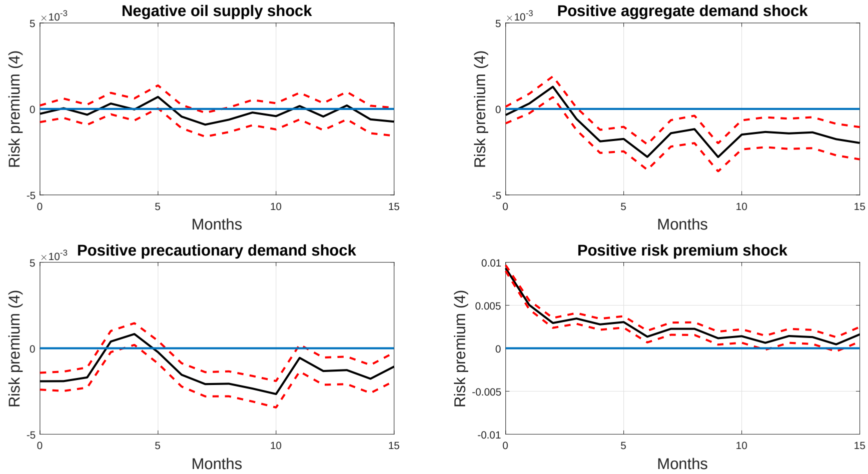
Finally, the impact response of the oil risk premium to a positive precautionary demand shock is negative. Overall, this shock causes a persistent decline in the oil risk premium, that can be motivated as follows.

First, the expected speculative gains (hence, the crude oil risk premium) decrease as current oil prices increase. This is consistent with the fact that higher oil prices require that speculators allocate more capital to purchase the same amount of contracts, causing the marginal value of the investment to decrease.

Second, when the term structure of the oil future curve is in contango, it is highly likely that a large number of speculators increases their long position in these contracts because they expect that the price of oil will be higher in the future. As a result, the rise in the speculative purchase of futures contract and hence, the competition among oil speculators, might cause a decline in the average prospective investment's return in the crude oil futures market.

Moreover, it is important to note that the decline in the risk premium might be reinforced by a reduction in the short-hedging demand of commercial firms. Although every hedging strategy implies an off-setting gain between spot and financial markets, it is well known that higher levels of oil prices might lead to a reduction of the incentive to hedge against price drops. This is motivated by a higher return than hedgers would receive if they did not hedge.

Figure 2.4: Median impulse responses of oil risk premium to each structural shock




*Note:* See Figure 2.3.

This conjecture is consistent with the view that crude oil risk premium is higher when net-short hedging demand is higher as discussed by Acharya and Ramadorai (2013). This implies that during a high level of oil prices an increase in the hedging supply from speculators and/or a reduction in the hedging demand from commercial firms might cause a reduction in the crude oil risk premium.

Third, the growing interests in commodity futures contract as an asset class for portfolio investment have attracted attention of many arbitrageurs causing the arbitrage profits to increase and the risk premium earned by oil speculators to decline, as discussed by Duffie (2010) and Etula (2013).

The average excess return of a crude oil futures investment consists of a spot return and a roll return. The spot return is simply the appreciation (or depreciation) of the futures contract held to maturity. The roll-return (or roll-yield) arises when investors want to maintain a crude oil futures position. This can be easily done, by selling the expiring contract and use the proceed to buy another futures contract for delivery at a more distant date.

In the case of backwardated market oil speculators can earn a positive roll-yield even if the spot price does not change. The roll-yield (and hence the crude oil risk premium received by oil speculators) could partially decline because of the arbitrageurs' attempt to profit from any possible mispricing triggered by index funds or other types of speculators during the rolling period.

Therefore, roll yield opportunities for commodity investors might cause a provisional reduction in the expiring futures price below its equilibrium. Conversely, the buying pressure of the next-to-expire contracts might cause a rise above the their economic fundamental prices.

As a result, the arbitrageurs attempt to profit from market price discrepancy through a long-short strategy. In other words, they can simultaneously short the nearby maturity contract and long the more distant one by earning a profit from the calendar spread. The arbitrageurs will close-out their positions by longing the short-maturity contract and shorting the long-maturity contract. Basically, the arbitrageurs' gain causes a drop in the crude oil risk premium which is mainly reflected by the decline in the roll-yield.

The empirical results shown in figure 2.4 represent valuable source of information for all investors who are interested in a long-only exposure to the price of oil. The global market for crude oil plays a primary role in determining the performance of commodity index traders or financial portfolios. Thus, understanding the path response of crude oil risk premium to unexpected changes in the price of oil can help how best to perform forward looking asset allocation analysis. In order to define a proper set of forward-looking efficient frontiers, oil speculators should combine assets weight and forecasts return at the net of the risk premium reduction, as documented in this analysis.

**Historical decomposition.** Figure 2.5 plots the historical decomposition of the crude oil risk premium and the real price of oil along with 68% posterior credible set.

There is empirical evidence that, from early 2003 until mid-2008, shocks to aggregate demand (likely driven by Emerging Asia and OECD countries) have represented the main economic factors behind the decline in the oil futures risk premium. This suggests that economic fundamentals represent the rational drivers behind any investment strategy taken on by speculators.

We would like to highlight that this finding remains consistent with the claim that the growth of commodity index investments have caused a reduction in the crude oil risk premium during the financialization of commodity markets. Interestingly, the historical effect of the risk premium shocks on the real price of oil is negligible. This result suggests that specific shocks to speculators (independent from the aggregate demand and/or supply of oil) were not the main factors in explaining the path of crude oil risk premium, during the financialization of commodity markets. This is consistent with the empirical results of Kilian and Lee (2014).

The role of speculation in driving the oil prices became important for policy implications when the spot price of oil dropped from historic highs of $130 in July 2008 to $33, five months later.

In the first half of 2008, figure 2.5 offers indication that the decline in crude oil risk premium was associated with an increase in the real price of oil mainly driven by shocks to precautionary demand for oil. The latter were likely triggered by some exogenous events in oil markets, as discussed by Smith (2009). For example, in March 2008 there was the sabotages of two main oil export pipelines in the south of Iraq, in April 2008 the strike of Nigerian union workers and finally, in June 2008 there was the closure of North Forties pipeline in UK and the mass rioting in Nigeria.

Figure 2.6 plots the hedging pressure indicator six months before crude oil reached a peak of $130 per barrel in July 2008, an all-time high.

The significant increase in the price of oil caused a reduction in the net-hedging demand from commercial firms followed by a decline in the crude oil risk premium paid to the speculators as a form insurance against down-trended prices. On the other side, higher oil prices required more money to invest in the futures market to buy the same amount of contracts. This caused a reduction in the crude oil risk premium.

Moreover figure 2.5 shows that positive precautionary demand shocks were partially responsible for the reduction of crude oil risk premium between 2010 and 2012. These shocks might be triggered by some concerns about international oil supply disruptions.

For example, Bastianin et al. (2017) discuss that Libyan civil war of February 2011 took about 1.5 million barrels per day off the global markets.

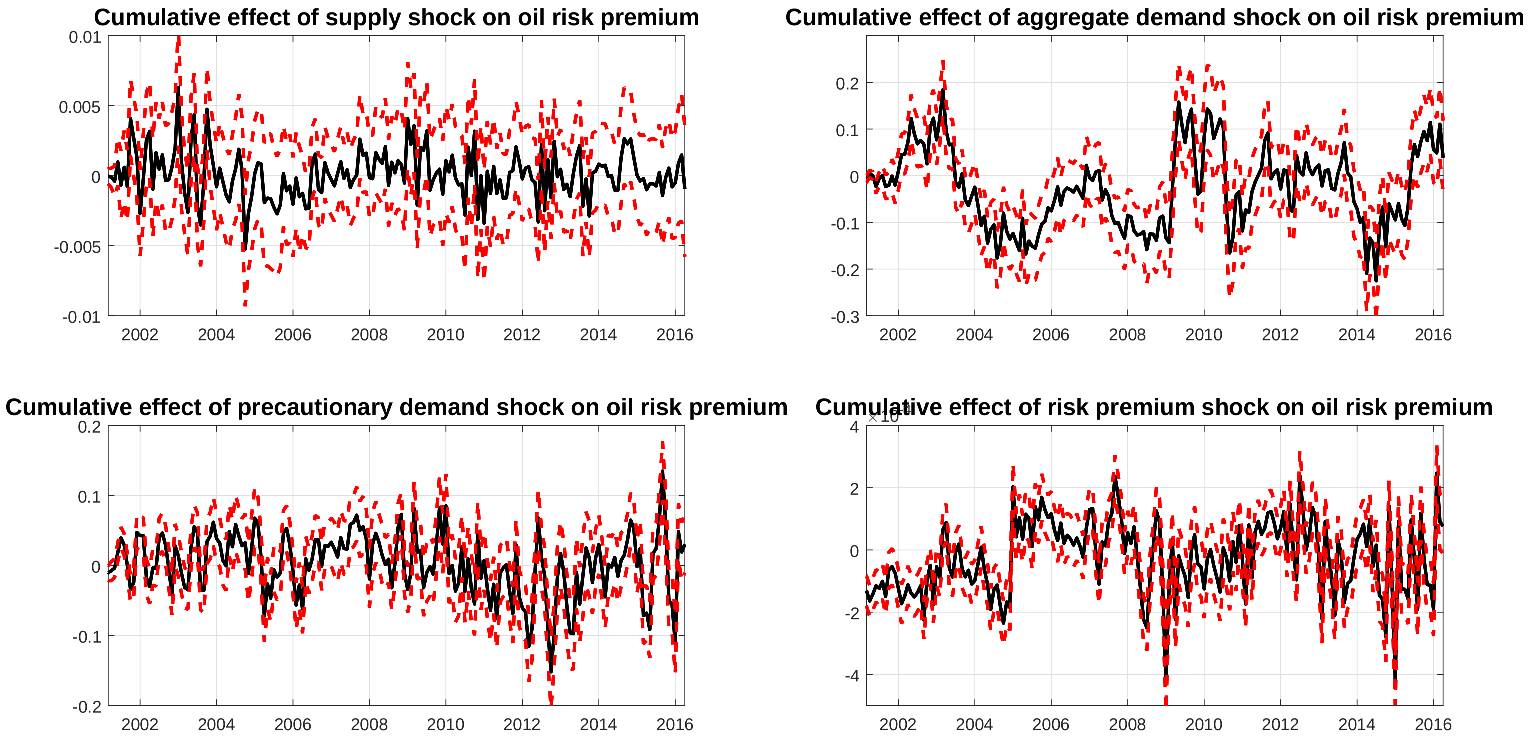
Moreover, the political tensions related to Iran's nuclear program lead to the European Union foreign ministers to agree on a ban on the transport, purchase and import into Europe of Iranian crude oil.

In early 2012 the Europe's sovereign debt crisis represented another possible factor that contributed to decline the crude oil risk premium through precautionary demand shocks.

On the other hand, a sequence of positive and negative aggregate demand shocks was responsible for high level of risk premium until the end of 2013. As a result the effect of precautionary and aggregate demand shocks on oil risk premium was offsetting.

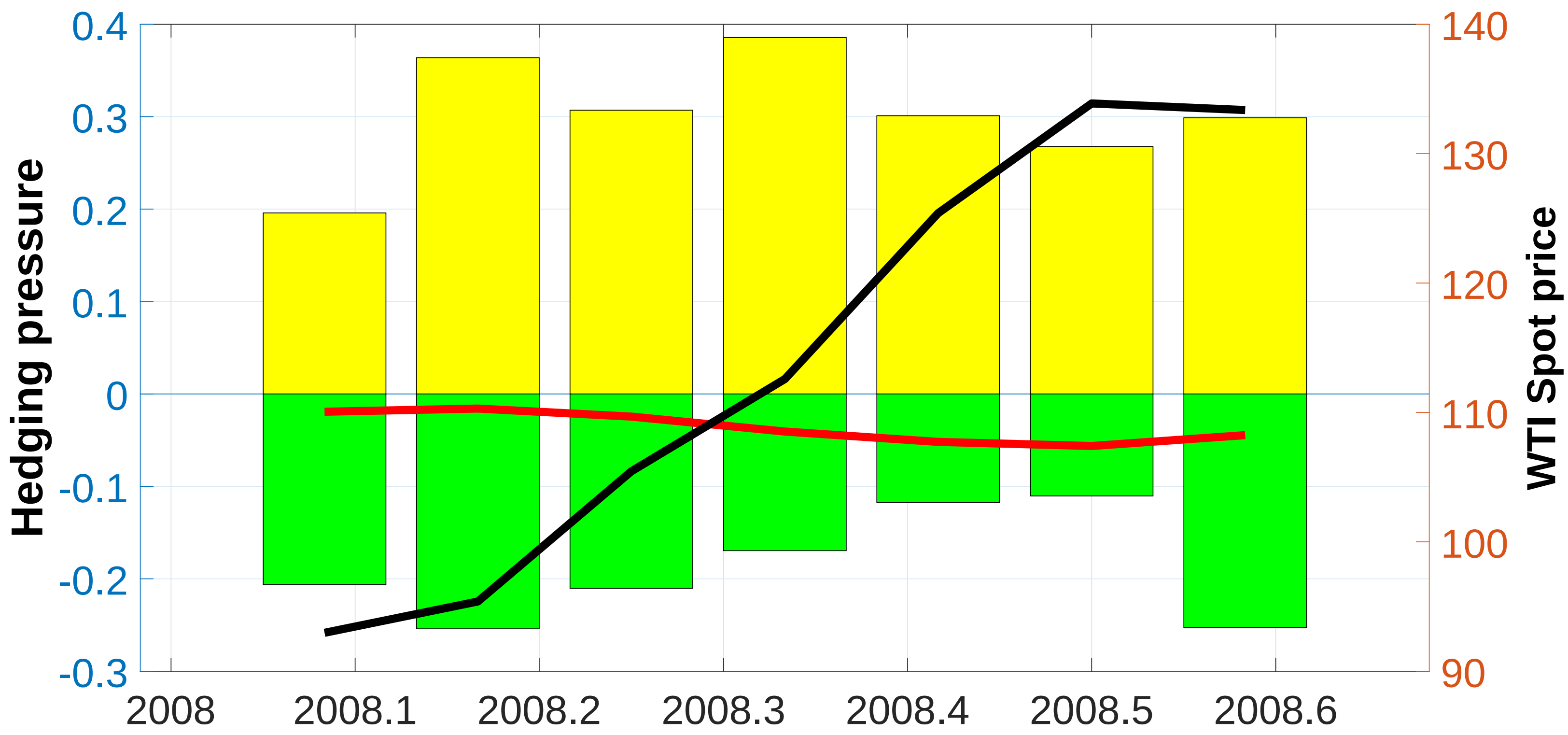
Between June and December 2014, the drop in the price of crude oil caused a systematic upward trend of the oil risk premium, which was mainly caused by a

Figure 2.5: Historical decomposition of crude oil risk premium




*Note:* Historical contribution of the structural shocks (black lines) with 64% posterior credible sets (red-dashed lines) implied by the identification structure of model 2.4.

Figure 2.6: Hedging pressure indicators.




*Note:* The reference period is January 2008 - June 2008. Solid black and red lines denote WTI spot price and the risk premium estimate ($rp^4_{t+3}$), respectively. Green bars refer to the net-hedging demand from commercial firms. Negative values indicate that hedgers are net-short. Yellow bars refer to the net-speculative demand from money managers. Positive values indicate that speculators are net-long.

combination of unanticipated positive shocks to the global oil production and negative aggregate demand shocks. The latter could reflect the unexpected slowdown in the global economy, likely driven by the decline in the Chinese manufacturing industry as reflected by the reduction in the level of Caixin manufacturing index.

## 2.6 Robustness checks

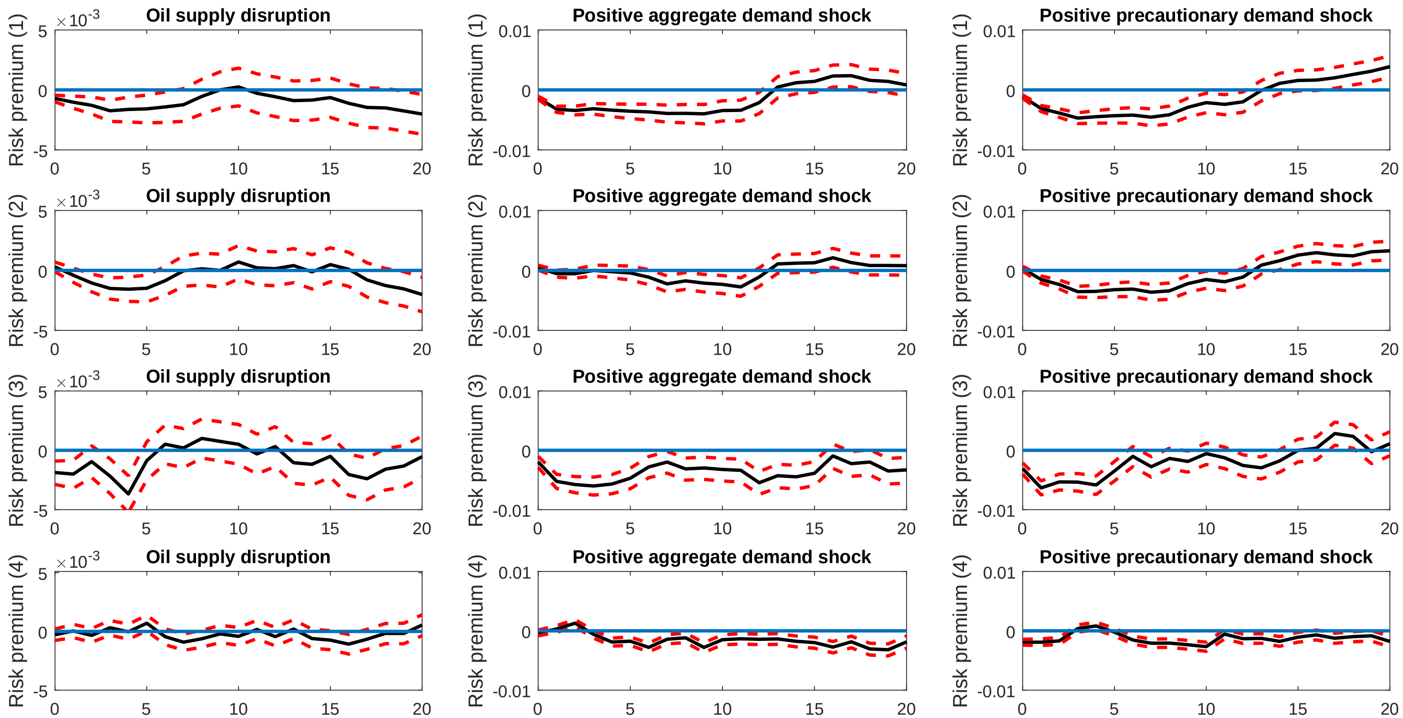
### 2.6.1 Alternative crude oil risk premium estimates.

The first robustness check relies on different estimates of crude oil risk premium, denoted by $rp^{(1)}_{t+3}$, $rp^{(2)}_{t+3}$ and $rp^{(3)}_{t+3}$. The latter are derived from the multivariate linear regression model, as reported in 2.3.1. In section 2.5 we have shown that the crude oil risk premium responds to oil price shocks differently, depending on the cause behind the shocks. This is also confirmed by figure 2.7. The latter plots the impulse response functions for each risk premium estimate.

An oil supply disruption (first column) causes a slight decline in the risk premium but much of the initial drop is reversed within the first ten months. Notice that, the impulse response functions of the first-three risk premium estimates to unexpected changes in global oil production, are somewhat larger than impulse response functions derived from futures prices only. A positive aggregate demand shock (second column), driven by unexpected fluctuation in the global business cycle, causes a large reduction in the crude oil risk premium. In general, during periods of strong economic growth we would expect to see a rise in the level of inflation. Although numerous studies document that commodity diversified portfolios represent one of the best ways to hedge against inflation risks our results suggest that the efficacy of this strategy could be adversely affected by the reduction in crude oil risk premium.

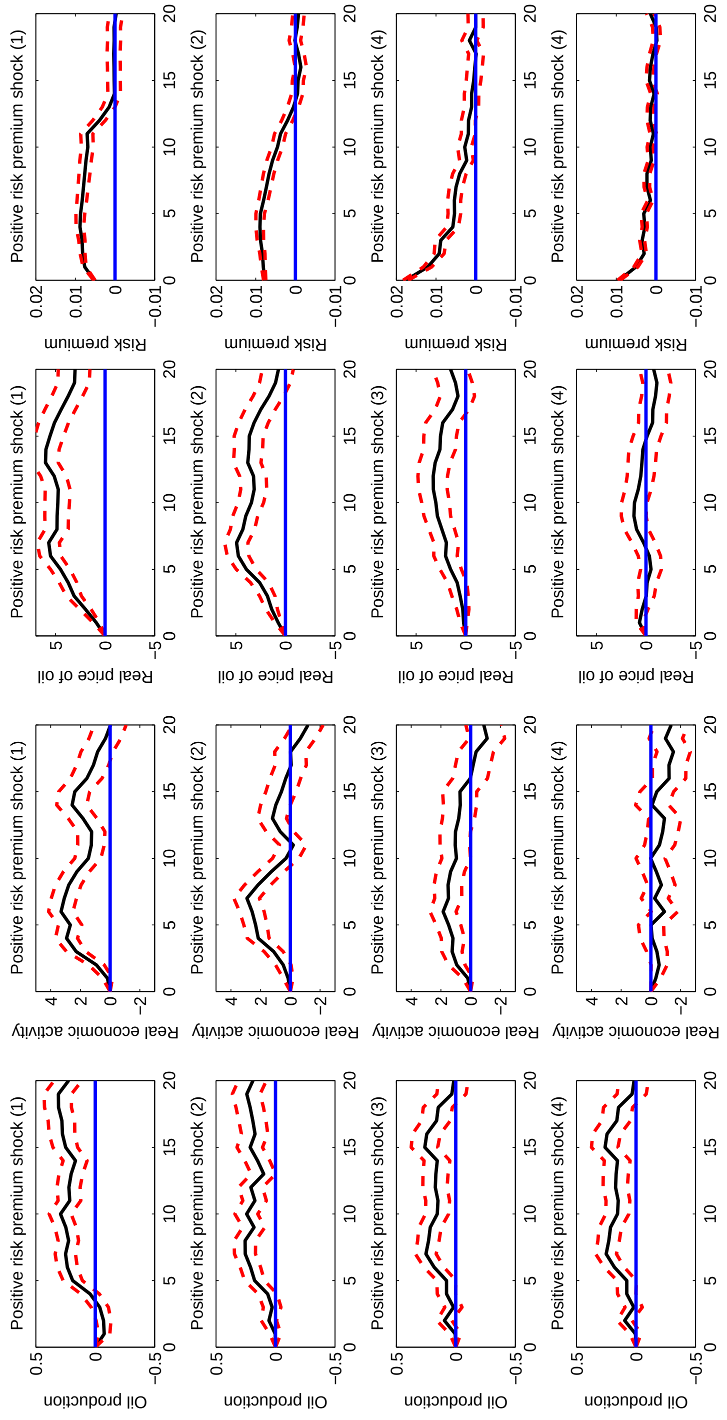
Finally, a positive precautionary demand shock causes a persistent reduction in all risk premium estimates. According to Kilian (2009) and Alquist and Kilian (2010) this shock might reflect an unanticipated increase in the demand for storage. The latter might provide useful information about what the term structure of futures prices will look like in the future.

Figure 2.7: Median impulse responses of risk premium estimates to oil market shocks




*Note:* See figure 2.3.

Figure 2.8: Median impulse responses of endogenous variables to risk premium shocks




*Note:* See figure 2.3.

Our results suggest that whenever the shape of the term structure is downward-sloping because of a positive precautionary demand shock the crude oil risk premium earned by a long investor could decline, even during backwardated futures market.

In sum, figure 2.7 provides evidence that impact responses of crude oil risk premium estimate to demand shocks are greater than supply shocks. Moreover, precautionary and aggregate demand shocks cause qualitatively similar results on the first-three risk measures of risk premium. Finally, figure 2.8 plots the median impulse response of the endogenous variables to different proxies for a positive risk premium shock.

The first piece of evidence is that the oil risk premium is the only variable to increase in response to unanticipated positive risk premium shocks.

Other macroeconomic and global oil market variables are not simultaneously affected by the risk premium shock, according to the identification structure implied by the model.

For this reason, risk premium shocks are not driven by economic fundamentals, as is typical of the global market for crude oil. For commercial firms positive shocks to the risk premium reflect a rise in the cost of hedging for reasons that are independent from the global market for crude oil.

Finally, figure 2.8 shows that an unanticipated positive risk premium shock might cause a rise in the cost of hedging for commercial firms. This would cause an increase in the price of oil beyond the impact period. It is important to point out that this result does not hold for every risk premium estimate. Therefore, we conclude that upon the impact period the effects of positive risk premium shocks on the real price of oil is mixed.

### 2.6.2 Alternative proxy for global real economic activity

The second robustness check relies on a different proxy for global real economic activity in order to assess the accuracy of our empirical findings. To this end, we estimate model 2.4 by replacing the Kilian's index ($rea$) with the growth rate of OECD+6 world industrial production index ($wip$). The latter allows us to exploit some prior beliefs on the income elasticity of oil demand given the methodology applied to recover the structural shocks.
In this respect, the contemporaneous structural matrix 2.9 can be re-written as:

$$A = \begin{pmatrix} 1 & 0 & -a_{q,p} & 0 \\ -a_{wip,q} & 1 & -a_{wip,p} & 0 \\ -a_{p,q} & -a_{p,wip} & 1 & 0 \\ -a_{rp,q} & -a_{rp,wip} & -a_{rp,p} & 1 \end{pmatrix} \tag{2.10}$$

We postulate that there is no direct feedback from changes in global oil production to changes in the industrial production, analogous to the benchmark model, discussed in section 2.4. Therefore, we put a *student t* prior distribution on $a_{wip,q}$ with mode at $c_{wip,q} = 0$, scale parameter $\sigma_{wip,q} = 0.2$ and degrees of freedom $\nu_{wip,q} = 3$.
Following Baumeister and Hamilton (2017), for the structural coefficient $a_{wip,p}$ we put a *student t* prior distribution with mode at $c_{wip,p} = -0.05$, scale parameter $\sigma_{wip,p} = 0.2$ and degrees of freedom $\nu_{wip,p} = 3$, truncated to be negative. The sign restriction on $a_{wip,p}$ reflects the economic beliefs that an increase in the price of crude oil causes a reduction in the industrial production. Finally, the structural parameter $a_{p,wip}$ governs the effect of changes in industrial production on the global price of crude oil. For an income elasticity of oil demand close to 0.7, the prior distribution function for $a_{p,wip}$ is a *student t* density with

mode at $c_{p,wip} = 2.1$ [6] , scale parameter $\sigma_{p,wip} = 0.2$ and degrees of freedom $\nu_{p,wip} = 3$, truncated to be positive. However, even the industrial production

Figure 2.9: Impulse response function of risk premium

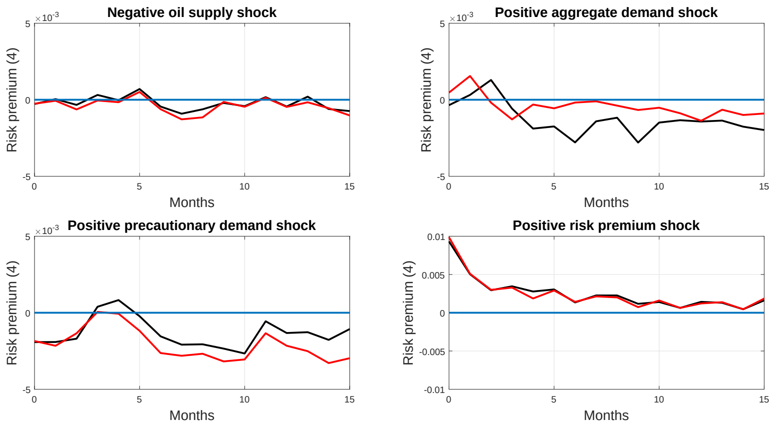
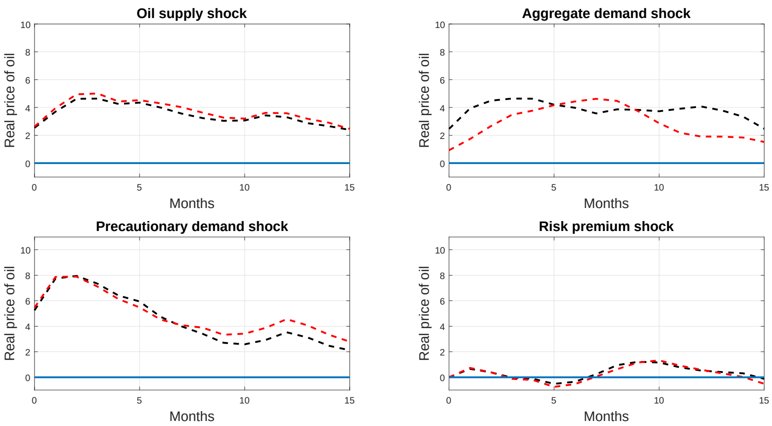



Figure 2.10: Impulse response function of real price of oil



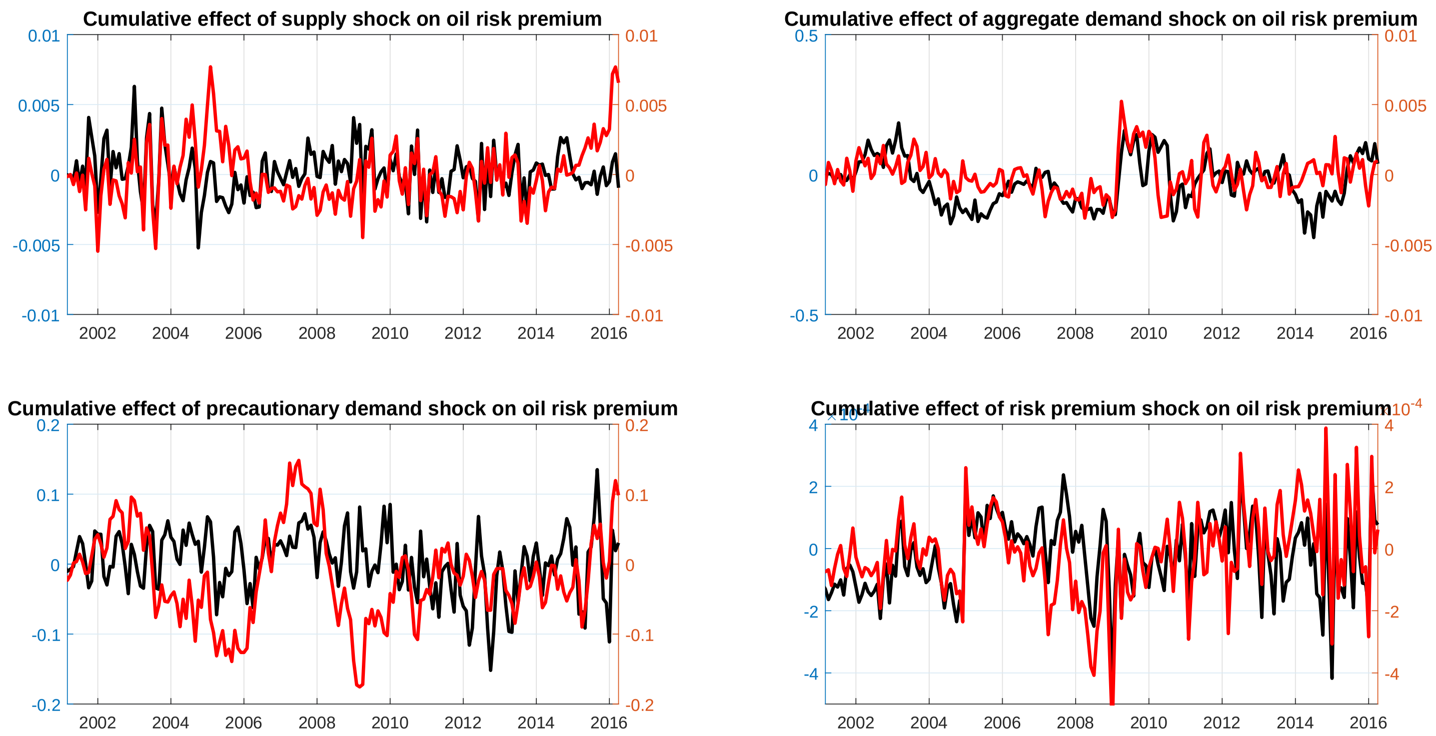

*Note:* Impulse response function of risk premium and real price of oil. Solid black and red lines refer to the impulse response function of risk premium to each structural shock implied by 2.9 and 2.10, respectively. Dashed black and red lines refer to the impulse response function of real price of oil for both 2.9 and 2.10 structural contemporaneous matrices.

index is not without shortcomings.

As pointed out by Kilian and Zhou (2017), the major OECD emerging

[6]Given the definition of income elasticity of oil demand, $\epsilon_{q_{oil},I} = \frac{\Delta Q_{oil}\%}{\Delta I\%} = \frac{\Delta Q_{oil}\%}{\Delta P_{oil}\%} \times \frac{\Delta P_{oil}\%}{\Delta I\%} = a_{q,p} \times a_{p,wip} = \frac{a_{p,wip}}{a_{p,q}} = a_{q,wip}$. Given a density function for the reciprocal price elasticity of oil demand ($a_{p,q}$) with mode at $c_{pq} = 3$ in absolute value, we need to put

Figure 2.11: Historical decomposition of crude oil risk premium for robustness check




*Note:* Historical contribution of the structural shocks. Black and red lines refer to cumulative effect of structural shocks on the risk premium implied by the structural contemporaneous equations of 2.9 and 2.10, respectively.

economies like China and India are not included in the index between 2003 and 2006.

Moreover, depending on the transformation applied to the industrial production index, the indicator does not provide a unique picture of the global business cycle. For example, log linearly detrended version of the index shows larger global economic slowdown than the same indicator taken in growth rate.

Figure 2.9 depicts the impulse response function of crude oil risk premium constructed under two different contemporaneous structural matrices.

Specifically, matrix 2.9 refers to the benchmark model and it takes into account the real economic activity index. Instead, matrix 2.10 includes the industrial production index and implies a positive impact response of risk premium to aggregate demand shocks. The effect of this shock is only temporarily and the impulse response of risk premium becomes negative after few periods.

Overall, the empirical response estimates of risk premium and real price of oil obtained from matrix 2.10 exhibit striking qualitative similarities with the empirical response estimates of the benchmark model.

Finally, figure 2.11 depicts the historical decomposition of crude oil risk premium, for the benchmark model (black line) and the alternative specification including the industrial production index (red line). We have shown that the average behaviour of the endogenous variables are robust to changes in the proxy for global real economic activity. In contrast, in case of the historical decomposition of crude oil risk premium, we highlight some differences that can be mainly attributed to the specific measures of economic activity. According to the SVAR model including the industrial production index (top-left corner of figure 2.11 ) the decline in actual risk premium $rp^4_{t+3}$ between 2005 and mid 2008 was mainly driven by cumulative effects of negative supply shocks (red

$c_{p,wip} = 2.1$ to get $c_{q,wip} = 0.7$.

line). The latter played an important role in driving up the risk premium over the last period. Finally, the role of aggregate demand shocks behind the recent drop in oil prices (and hence increase in the risk premium) is negligible (red line) compared to the same effect implied by the benchmark model with real economic activity index (black line). As regards the importance of the risk premium shocks, both specifications agree that residual shocks have not been relevant in driving the risk premium estimates (bottom-right corner of figure 2.11) over the period of interest.

## 2.7 Conclusions

The benefit of including oil futures contracts as an asset of financial investment portfolio is widely accepted in both the academic literature and the oil industry.

Crude oil futures contracts allow investors to get more attractive portfolio's diversification with a higher ratio of return to risk than traditional investments made of equities and bonds, only.

Therefore if the current futures price is below the expected future spot price, arbitrage mechanism implies convergence of the futures price to the spot price at maturity and this turns into positive excess returns.

The expected returns of crude oil futures investment represent simply bets because spot and roll returns follow an uncertain scenario. However, a possible way to derive a forward-looking measure of risk premium relies on the impulse response estimates implied by the SVAR model proposed in this analysis.

Moreover, impulse response analysis suggests the existence of a negative relationship between the impact responses of the real price of oil and oil futures risk premium to shocks of the economic fundamentals of the global oil market. As a consequence investors could exploit these findings as an asset allocation strategy.

Finally, we highlight that the main economic factors behind the historical decline of the risk premium can be explained by shocks to aggregate and precautionary demand for crude oil.

In this way the effects of the financialization of commodity markets on the risk premium are modelled endogenously with respect to the global market for crude oil.

Our results suggest that shocks to economic fundamentals play a crucial role in explaining the path of the oil futures risk premium. They are also more important than specific shocks to the non-diversifiable component of the long investors.

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# Appendix Chapter 2

## 2.8 Identification strategy

This section reports a short description of the algorithm proposed by Baumeister and Hamilton (2015) for the estimation of model 2.4, under a Bayesian perspective. The implementation of the estimation algorithm is based on three main steps.

First stage consists of a specification of informative prior beliefs, represented in form of density functions about the matrix $A$, the vector collecting the structural disturbances $v_t$ and the matrix $B_j$, for $j = 1, \cdots, 12$.

Prior for the elements of the contemporaneous structural matrix that are not known with certainty are collected in a vector ($\alpha$). Thus, let $p(A)$ be the joint prior distribution which is made by the product of *Student t* distributions of the elements collected in $\alpha$. Then, we need to specify priors for the inverse diagonal elements of the variance-covariance matrix of the structural errors $D$ conditional on $A$. The priors for $d_{ii}^{-1}$ (which denotes the element in row and column $i$ of matrix $D$) conditional on $A$ is given by a $\Gamma(\kappa_i, \tau_i)$ distribution, as follow:

$$p(D|A) = \prod_{i=1}^{n} p(d_{ii}|A) \tag{2.11}$$

where $\kappa_i/\tau_i$ and $\kappa_i/\tau_i^2$ represent the first and second moments of $d_{ii}^{-1}$, respectively. Notice that, the parameter $\tau_i$ depends on $A$ whereas $k_i$ does not.

Following Baumeister and Hamilton (2015) we calibrate the diagonal elements of $D$ from the residuals obtained by running ols regressions from the univariate autoregressive models of order 12. Moreover, we set the prior mean for $d_{ii}^{-1}$ equals to the reciprocal of the diagonal element of a matrix $ASA'$, where $S$ represents the sample variance covariance matrix of the univariate autoregressive models performed for each time-series.

We postulate $\tilde{b}_i$ is a row vector of random structural coefficients following a conditional normal multivariate distribution, $\tilde{b}_i|A, D \sim \mathcal{N}(m_i,\, d_{ii}M_i)$ where $m_i$ can be interpreted as the best guess about $\tilde{b}_i$ before seeing the data and $M_i$ represents the level of uncertainty about the standard Minnesota prior.

We follow the approach proposed by Doan et al. (1984) in which the behaviour for a generic time-series can be represented by a random walk process with $m_i = 0$ and great confidence to expect that coefficients related to higher lags are zero. [7]

In the end, the joint probability distribution of the prior information about the plausible values of the parameters is defined as:

$$p(A, D, B_j) = p(A)p(D|A)p(B_j|A, D) \qquad \text{for } j = 1, 2, ..., 24 \tag{2.12}$$

In the second step, the Baumeister and Hamilton (2015)'s algorithm searches for a vector of values $\hat{\alpha}$ that solves numerically a maximization problem of the target function $q(\alpha)$. Thus, the vector $\hat{\alpha}$ provides a reasonable guess for the

[7] Following Baumeister and Hamilton (2017) we need to set three different values for the hyper-parameters of the random walk prior for the lagged coefficients. Thus, we set the parameter controlling the overall tightness of the prior to 0.5. We set the parameter that governs how quickly the prior for lagged coefficients tightness to zero as lag increase to 1. Finally, we put prior on the parameter governing the tightness of the prior for the constant term to 100. The latter is used to make the prior on the constant term irrelevant.

posterior mean of $\alpha$ while the matrix of second derivatives of $q(\alpha)$ with respect to $\alpha = \hat{\alpha}$ exploits information about the shape of the posterior distribution of $\alpha$.

In other words, the second stage sets the initial values for the elements of $A$ in order to inform the random-walk Metropolis Hasting algorithm, that is performed in the third step.

The last stage is designed to construct the joint posterior distribution of the parameters, that is $p(A, D, B|Y_T)$, where $Y_T$ represents the sample-data. According to Baumeister and Hamilton (2015) we proceed as follow.

First, we use the Metropolis Hasting algorithm to generate draws from the posterior distribution of the contemporaneous structural matrix, that is $p(A|Y_T)$. The iteration starts setting $\alpha^1 = \hat{\alpha}$ and for a generic step $l+1$ we generate a candidate $\tilde{\alpha}^{(l+1)}$ as a sum of $\alpha^l$ and the product between three components: (1) a vector of independent standard *student t* variables with 2 degrees of freedom, (2) a scalar tuning parameter for 30% acceptance ratio and (3) the Cholesky factorization of the matrix capturing the curvature of the posterior distribution of the vector of unknowns parameters $A$.

Then, we compare the value of the target function evaluated in $\tilde{\alpha}^{(l+1)}$ and $\alpha^{(l)}$, respectively. If $q(\tilde{\alpha}^{(l+1)}) < q(\alpha^{(l)})$, we set $\alpha^{(l+1)} = \alpha^{(l)}$ with probability $1 - exp[q(\tilde{\alpha}^{(l+1)} - q(\alpha^{(l+1)})]$; otherwise we set $\alpha^{(l+1)} = \tilde{\alpha}^{(l+1)}$. The value $l$ indicates the number of iterations with the first $D$ burn-in draws included. Thus, starting with $l = D + 1$, for each $\alpha^l$ we generate $\delta^l_{ii} \sim \Gamma(k^*_i, \tau^*_i(A(\alpha^l)))$ for $i = 1, 2, 3, 4$ and take $D^l$ to be diagonal matrix whose elements $d^l_{ii} = 1/\delta^l_{ii}$.

Finally, from the posterior distribution of the variance covariance matrix of the structural error terms we can further generate $\tilde{b}^l_i \sim \mathcal{N}(m^*_i,\, d^l_{ii}M^*_i)$ for $i = 1, 2, 3, 4$, where $\tilde{b}^l_i$ is the row vector of lagged structural parameters referred to the $i$th variable.

In the end, the triple $\{A(\alpha^l), D^l, B^l\}_{l=D+1}^{D+N}$ represents a sample size $N$ of posterior distribution:

$$p(A, D, B|Y_T) = p(A|Y_T)p(D|A, Y_T)p(B|A, D, Y_T)) \tag{2.13}$$

with the first $D$ burn-in draws equals to 200.000 and $N = 200.000$.

# Conclusions

Identifying and understanding the economic fundamentals behind changes in the price of oil is not a simple endeavour.

On the basis of the theory of storage, traditional oil market VAR models include a proxy for global petroleum inventories. This represents a physical measure that plays a crucial role in identifying speculation activities in the physical market for crude oil.

In addition, standard arbitrage assumptions provide an equilibrium between the two markets even if a measure of the forward market is not explicitly included in the analysis. As a result, if a speculative purchase drives the oil futures price up, the arbitrage mechanism ensures that oil traders buy inventories in the physical market, causing the spot price of oil to rise. Most VAR models existent in the literature, do not support the role of speculation in driving oil prices during the financialization of commodity markets. Therefore, the first chapter of my dissertation sheds light new on evidence regarding this subject.

Following the theory of storage, I highlight the advantages and roles played by the oil futures-spot spread -as an alternative measure of the proxy for global oil inventories- to infer the forward-looking expectations of oil traders. In other words, I provide an economic meaning for the residual structural shock which is able to capture the effects of the oil price speculation that is driven by financial incentives to keep oil off the physical market.

As a result, the speculation that has been identified by oil market VAR models specified a' la Kilian and Murphy are conceptually different from this new shock, called financial market shock. While both shocks are designed to capture an instantaneous increase in the amount of oil stocks for future consumption, the main difference stems from the value of holding oil inventories.

In the first case, the inventories' build-up is explained by an increase in the demand for storage. This causes an instantaneous reduction of the oil futures-spot spread, which is mainly driven by a rise in the convenience yield. In the second case, the accumulation of crude oil inventories causes an increase in the oil futures-spot spread which is mainly explained by a decline in the convenience yield.

The main results from the model proposed in the first chapter provides empirical evidence that financial market shocks have contributed to explain the rise in the price of oil during the financialization of commodity markets. However, in explaining the sharp rise in the price of oil, I found that shocks to the aggregate demand remain the main important drivers in accordance with previous studies.

Another important topic consists of the impact of oil price shocks on economic and financial indicators. In particular, in the second chapter I investigate the connection between unexpected changes in the global price of oil and oil futures risk premium estimates.

Impulse response analysis suggests the existence of a negative relationship between the impact responses of the price of oil and of the oil risk premium to shocks of the economic fundamentals in the global market.

The results show that the crude oil risk premium responds to oil price shocks differently, depending on the causes behind the shocks. In particular, the response of the crude oil risk premium to demand shocks is greater than the supply shocks.

As a consequence, investors could exploit these findings as an assets allocation strategy. Thus, in order to define a proper set of forward-looking efficient frontiers, oil speculators should combine assets' weight and expected return at the net of the risk premium reduction, as documented in this analysis.

Moreover, it is important to note that the decline of the risk premium might be reinforced by a reduction in the short-hedging demand of commercial firms. Although every hedging strategy implies an off-setting gain between spot and financial markets, it is well known that higher levels of oil prices might lead to a reduction of the incentive to hedge against price drops. This is motivated by a higher return than hedgers would receive if they did not hedge.

Other interesting results refer to the effects of a positive risk premium shock on the set of endogenous variables.

The first piece of evidence is that the oil risk premium is the only variable to increase in response to positive risk premium shocks. Other macroeconomic and global oil market variables are not simultaneously affected by the risk premium shock, according to the identification structure implied by the model. For this reason, risk premium shocks are not driven by economic fundamentals, as is typical of the global market for crude oil.

Beyond the impact period, an unanticipated positive risk premium shock might cause a rise in the cost of hedging for commercial firms and an increase in the price of oil. It is important to point out that this result does not hold for every risk premium estimate. Therefore, we conclude that upon the impact period the effects of positive risk premium shocks on the real price of oil is mixed.

Last but not least, this paper provides results in terms of the historical decomposition of the crude oil risk premium. There is empirical evidence that shocks to the aggregate demand represent the main economic factors behind the decline of the oil futures risk premium. This implies that, economic fundamentals represent the rational drivers behind any investment strategy taken on by speculators, with direct impact on the aggregate measure for crude oil risk premium. It is important to point out that, this finding is still consistent with the claim that the growth of commodity index investments have caused a reduction in the crude oil risk premium.

In general, my dissertation expands current empirical literature on two fields regarding the global market for crude oil. The first refers to modelling the price of oil, while the second consists of the impact of oil price shocks on economic indicators.

The goal of research in the first field is to identify the aggregate contribution of the main economic and financial factors behind changes in the price of crude oil. Given the complexity of the issue, this analysis could lead to further investigation along two main lines: (1) the type of variables and (2) the methodology used for the empirical analysis.

As regards the first issue, researchers should find alternative variables to capture the forward looking expectations of oil traders. In this work I introduce a proxy for the convenience yield that derives from the futures market but is not the only measure available. One might decide to use other derivative contracts to infer a forward-looking measure.

Moreover, I think that the interaction between oil futures prices and changes in crude oil inventories deserve further investigation. Recently, “the financial and physical oil markets linkages” was the main topic discussed in the workshop organized by the EIA.

The empirical work proposed by Miao et al. (2017) provide an important contribution to the investigation of the impact of crude oil inventory announcements on derivative prices. The authors state that: *oil futures and options prices respond in a manner that seems to "correctly" anticipate changes in oil inventory levels - anticipatory trading apparently prevails -*. It should be interesting to conduct an analogous investigation by taking into account the endogeneity of the variables.

The second issue refers to the econometric framework used to carry on the empirical analysis. I suggest adopting a factor-augmented VAR model (FAVAR), as discussed in Juvenal and Petrella (2015), because an analysis based on panel-data, economic factors and a proper identification scheme might improve the accuracy of the results.

The second chapter of the thesis investigates the role of the oil futures risk premium in the international market for crude oil. This analysis emphasises the importance of the risk premium for two main reasons. First, it represents the opportunity cost that is accrued to commercial firms for hedging purposes. Second, it is an attractive investment return for oil speculators. This is motivated by the inflow of capital into crude oil futures markets from commodity index traders. The latter are economic agents who wish to gain exposure to the oil futures price without holding the commodity in the physical market.

This analysis suggests a number of avenues for future research.

First, since the risk premium is not observable, more advanced models should be adopted for its estimation. For example, a new class of financial models called "unspanned macroeconomic factor models" should be introduced to this field. Basically, they are linear affine term structure models that are similar to those proposed by Casassus and Collin Dufresne (2006) and Hamilton and Wu (2014) except for the role played by the economic activity in explaining the risk premium. In fact, linear affine term structure models suffer from several limitations due to the "spanning hypothesis". This implies that all relevant information of the economy is spanned, that is reflected by the current futures price. As a consequence, further information from the business cycle does not contribute significantly to improve the forecasting accuracy of the oil futures price and the implied risk premium.

As opposed to these methodologies, results from unspanned models that explicitly link the real economic activity with the oil financial markets help to improve forecasts of oil futures prices, like in Alquist et al. (2014) and Heath (2016).

Another way to retrieve reliable risk premium estimates is to adopt a forecasting combination approach. In its simplest form, this method consists of a weighted average of risk premium estimates which are derived from a combination of different econometric approaches, like the above mentioned risk premium regression and unspanned models.

Finally, this analysis, along with other recent research, suggests that interpreting the role of the risk premium requires the identification of the channels through which oil shocks can affect the economy. Since recent studies by Hamilton and Wu (2012, 2014) have documented an increase in the volatility of the oil futures risk premium, the empirical literature should focus on SVAR models, identified via heteroskedasticity. Alternatively, researchers might propose other advanced approaches that take into account the shifts in the regimes of the stochastic process driving endogenous variables, as the Markov switching VAR models do.